ANALYSIS OF INPATIENT HOSPITAL STAFF MENTAL WORKLOAD BY MEANS OF DISCRETE-EVENT SIMULATION

THESIS

Erich W. Maxheimer, 2d Lieutenant, USAF

AFIT-ENV-MS-16-M-166

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENV-MS-16-M-166

ANALYSIS OF INPATIENT HOSPITAL STAFF MENTAL WORKLOAD BY MEANS OF DISCRETE-EVENT SIMULATION

THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Systems Engineering

Erich W. Maxheimer, BS

2d Lieutenant, USAF

March 2016

AFIT-ENV-MS-16-M-166

ANALYSIS OF INPATIENT HOSPITAL STAFF MENTAL WORKLOAD BY MEANS OF DISCRETE-EVENT SIMULATION

Erich W. Maxheimer, BS

2d Lieutenant, USAF

Committee Membership:

Maj C. F. Rusnock, PhD
Chair

Lt Col K. F. Oyama, PhD
Member

Maj V. V. Valencia, PhD
Member

AFIT-ENV-MS-16-M-166

Abstract

Many process improvement tools have been applied to the healthcare industry to improve safety and efficiency. However, nearly all of these tools have neglected to explicitly quantify mental workload of healthcare providers despite the consensus that it is related to human performance. This research uses the Improved Performance Research Integration Tool (IMPRINT), a discrete-event simulation (DES), to quantify mental workload. Specifically, this research examines staff members in an inpatient unit at the Wright-Patterson Medical Center to detect workload differences between staff, identify trends which lead to high workload demands, evaluate the influence of patient load on mental workload, and test a workload-leveling process improvement. Results from this study indicate workload differences between staff types and finds that task urgency and complexity play a role in the overloading of tasks. The relationship between predicted mental workload and increased patient load is mostly linear; however, the slopes are different between staff types, indicating that staff types are predicted to be affected unequally by increases in patient demand. Lastly, the task sharing process improvement provides mixed results; idle time and average workload become more balanced, but overload time becomes more unbalanced. Overall, this study demonstrates the usefulness of IMPRINT at evaluating medical systems.

Acknowledgments

Firstly, I would like to extend my sincere appreciation to my advisor, Maj Christina Rusnock for her selfless guidance and support over the course of my time at AFIT. I also thank my committee members, Lt Col Kyle Oyama and Maj Vhance Valencia, for sharing their expertise and providing direction. I would, also, like to thank Lt Col Jared Mort and the 88th Medical Group, Medical Surgical Unit; this research would not be possible without them. Finally, I would like to thank my wife for her nonstop love and support throughout this process.

Erich W. Maxheimer

Table of Contents

List of Figures

List of Tables

List of Equations

Page

ANALYSIS OF INPATIENT HOSPITAL STAFF MENTAL WORKLOAD BY MEANS OF DISCRETE-EVENT SIMULATION

I. Introduction

Chapter Overview

This chapter begins by introducing two main concerns about the United States healthcare system. Issues with Veterans Affairs (VA) Medical Centers are addressed and a consortium with the VAs in Ohio and the Wright-Patterson Air Force Base, 88th Medical Group is introduced. The chapter then explains how discrete-event simulation (DES) can aid in consortium planning and hospital process improvements. Research and investigative questions are presented to address the research problem. A course of action for answering the questions is described, followed by assumptions, expected contributions, and a preview of the remaining chapters.

Background

The aging population in the United States is a looming threat over the national healthcare system. By 2030, at least 20% of Americans will be 65 or older (Colby & Ortman, 2014). A growing senior citizen population puts stress on the healthcare system because they are susceptible to injuries and illnesses. At the same time that the aging population is expected to put the most pressure on the healthcare system, many healthcare professionals are set to retire (Center for Health Workforce Studies School of Public Health, 2006). These combined factors require the remaining healthcare workers to take

on more work which could lead to low human performance and higher rates of medical errors.

The healthcare system is already experiencing problems with preventable medical errors, which cause an alarming number of deaths and injuries each year. A study using data from 1984 estimated that 98,000 Americans die each year from medical errors (Kohn, Corrigan, & Donaldson, 1999). A more recent study using data from 2008-2011 estimated that the number of deaths from medical errors rose to 400,000 (James, 2013). Unless changes are made, it is likely that the number of preventable medical errors will increase as the demands on the healthcare system increase. The healthcare system needs to be evaluated and improved before the situation gets any worse.

Research Problem

The healthcare issues faced at the national level affect Veterans Affairs (VA) Medical Centers. In recent years, the VA Medical Centers have had a particularly difficult time keeping up with patient demand. As of November 2014, 600,000 (10%) of VA patients were forced to wait more than a month for appointments (Hoyer & Brook, 2014). The VA has been under pressure by Congress to improve wait times and has made progress by hiring more employees and sending some patients to private providers. In Ohio, VA wait times are being addressed, in part, by the Buckeye Federal Healthcare Consortium. The consortium allows some VA patients to seek treatment at the Wright-Patterson Air Force Base, 88th Medical Group, Medical Center for the next five years. Typically, healthcare services from active duty military treatment facilities, like the one at Wright-Patterson Air Force Base, are reserved for active military members, their

dependents, and military retirees. The consortium creates a new medical resource for the VA system. Allowing veterans to use the Wright-Patterson Medical Center should shorten patient wait times through the normal VA medical system and cost less than sending them to private hospitals.

According to a Clinical Nurse Specialist, the 88th Medical Group is expecting a 30% increase to inpatient units and 20-25% increase to outpatient clinics as a result of the consortium (Mort, 2015). The 88th Medical Group needs to ensure that the increase in patients will not significantly increase medical staff mental workload, which could reduce the quality of patient care. Process improvements like workload leveling, standardization, or waste reduction are being considered to improve efficiency and proactively prepare the facility for the patient load increases. To effectively implement process improvements, the processes in the Wright-Patterson Medical Center need to be analyzed.

A powerful method to evaluate systems and to test process improvements is through discrete-event simulations (DES). DES is more useful than simple flow diagrams or heuristics because it can test multiple alternate scenarios in short amounts of time. DES models of hospital units have been the topic of many research studies (Gunal & Pidd, 2010). All hospital DES models found during this investigation (Duguay & Chetouane, 2007; Ferrin, Miller, & McBroom, 2007; Komashie & Mousavi, 2005) use time-based metrics like bed wait times, throughputs, or length of stay to evaluate a system. Time-based metrics are useful in some situations; but, they usually fail to consider the human component of a system which may be the limiting factor. Some DES software packages are able to evaluate the human element of a system based on mental

workload. Quantifying mental workload using DES can be very useful for evaluating systems; however, this method is not yet widely used for hospital systems.

Research Objectives

There are two main objectives to this study. The first is to use the Improved Performance Research Integration Tool, (IMPRINT) in a novel way to quantitatively model the mental workload of healthcare staff and which can serve as an example for future healthcare research. The second objective is to provide information which can aid process improvements at the 88th Medical Group in preparation for an increased patient load. These objectives are fulfilled by evaluating the mental workload of inpatient medical staff under large patient load increases. After an initial investigation, the researchers propose and test a potential process improvement opportunity.

Research and Investigative Questions

The following research question was developed to fulfill the two research objectives: What is the impact of an increased patient load on medical staff mental workload in the 88th Medical Group, Medical Surgical Unit (MSU)? To fully answer this question, the following three investigative questions are addressed:

1. What is the relationship between patient load and medical staff mental workload metrics (idle time, average mental workload, overload time)?
2. Which medical staff workers experience the greatest negative impact in mental workload metrics as patient load increases?
3. How does patient load influence individual task performance (total task times and overload task times)?

The first investigative question is used to determine if the relationships between patient load and workload metrics are linear or non-linear. If the relationships are non-linear, the researchers will determine if the slopes are concave or convex and the locations of slope changes. The second investigative question is used to determine if the relationship between patient load and the workload metrics are different between staff types. If they are different, the researchers will determine which staff types have the greatest slope. Since IMPRINT does not directly provide information on the quality of task performance, the third investigative uses total task time and overload task time to infer the quality of task performance. Increases to the overload time of tasks infers lower task performance. The researchers use the answers to these investigative questions to propose and test a potential process improvement opportunity.

Methodology

The investigative questions are evaluated using the DES program, IMPRINT. IMPRINT is developed by ALION and is funded by the Army Research Lab (Alion Science and Technology Corporation, 2015b). It is specifically used because of its workload modeling capabilities. Important tasks performed in the MSU are modeled in IMPRINT. Creating the model requires task analyses, direct observations, and data collection. Real-world medical records are also used. Subject matter experts (SMEs) estimates are used for data which are determined to have little impact on results or are unattainable given resource limitations. Staff member personally identifiable information (PII) is limited to names, job titles, and years of experience. Patient PII is limited to admission and discharge dates and times. This research is exempt from the institutional

review board (IRB) human experimentation requirements. For further details, reference the IRB exemption letter in Appendix B – IRB Letters.

Assumptions/Limitations

Ideally, models are built with just enough detail to answer the research questions of a study. Including too much detail adds little value and is a waste of effort and resources. Additionally, there is some information which is impossible or not worth the cost of collecting. For this reason, assumptions are usually used for simplification purposes. There are four global assumptions made for this study. The first assumption is that SME estimates are accurate approximations to real-world data. This assumption is justified because SMEs have cared for thousands of patients which help them to make accurate estimates. The second assumption is that any data collected during observations are representative of normal conditions. Due to the Hawthorne Effect, the medical staff may act differently when they are being watched. The researchers will work to reduce this effect by informing the medical staff that their information will remain confidential and asking them to act like they normally would. A third assumption is that VA patients are comprised of the same proportion of types and acuity of current patients which have historically used the MSU. It is likely that the VA patients will have different illnesses and acuities, but the differences between them and past patients are not known to the researchers. The final global assumption is that the MSU is isolated from the effects of other units. An increase in VA patients may have effects to other parts of the Wright-Patterson Medical Center which may indirectly effect the MSU. These effects are unknown. While the four global assumptions are the most important, Appendix E –

Assumptions and Justifications includes the complete set of assumptions. The majority of the remaining assumptions are specific to the model used for this research.

Expected Contributions

This research is expected to have significant applied and theoretical applications. The results provide valuable information to the Wright-Patterson Medical Center about the mental workload of MSU staff members under current and future scenarios. Specifically, this study gives an understanding of how medical staff mental workloads are influenced by large patient load increases, which the medical center is expecting. This information is expected to be used to proactively inform policies and process improvements to save lives, reduce injuries, and improve patient and staff satisfaction.

The theoretical applications of this research benefit the research community by being the first to use simulation to quantitatively model the mental workload of medical staff members. The methodology and proven benefits of this research may spark future researchers to perform similar studies on other medical systems and expand on this research. Ultimately, this research has the potential to benefit countless patients and medical staff members at a local and national level.

Preview

This research follows the scholarly format, thus some of the chapters are self-contained drafts of potential publications. Chapter II contains a literature review from relevant sources on the topics of DES and mental workload in healthcare. Chapter III explains how the IMPRINT model was created and evaluates the MSU under current conditions. Chapter IV evaluates the MSU under increased patient loads and answers the

three investigative questions. Chapter V uses the answers to the investigative questions to propose a potential process improvement opportunity which is tested using IMPRINT. Chapter VI contains a summary of the research results and future research recommendations.

II. Literature Review

Chapter Overview

This chapter provides background information on important topics which apply to this research. It begins by describing why and how process improvements are used in healthcare. It then describes how simulations are used in healthcare and the most popular simulation tool which have been used. The chapter dives deeper into discrete-event simulations (DES) by explaining how it has been used, the benefits of using it compared to other operations research methods, and its limitations. Finally, a DES tool which is able to quantitatively model mental workload of workers is introduced. The researchers explain how mental workload is an important metric to model; yet, it has not been modeled in the healthcare industry. The chapter concludes by stating the research gap and providing a summary.

Process Improvements in Healthcare

As presented in the introduction chapter, the United States healthcare system is facing increasing demands and is in need of process improvements to improve performance. Deming (2000) and Scholtes, Jointer, & Streibel (2003) postulate that over 90% of performance issues in systems can be traced back to poor system design.   In the medical field, poorly designed systems can result in poor patient satisfaction, increased expenses due to waste, and medical errors. The high stakes and room for improvement make process improvements an effective tool for the United States healthcare system.

There are many different principles and tools to guide process improvement initiatives. In general, process improvements are any strategic method which aims to

improve the efficiency of a system. Before making improvements, specific quality characteristics of a system which are to be improved should be targeted. The quality of any system is defined by the customer (Carey & Lloyd, 1995). In healthcare, the customers are patients who are usually concerned with things like wait times, costs, outcomes, and safety.

After defining the quality characteristics which are to be improved, process improvement should work to identify problems impacting these qualities. Pareto's principle is the idea that the majority of the problems in a system are from a few critical causes (Carey & Lloyd, 1995). There are countless ways in which systems can be changed; however, many of these changes may not address the root problems or may cause unintended consequences. Therefore, good process improvements dig deep to investigate the root problems in a system.

Simple methods to identify root problems involve the five whys, fishbone diagrams, value stream mapping, and process flow charts (Liker, 2004). These methods are useful for most process improvement initiatives and are simple enough for any manager to implement. Sometimes, more sophisticated methods like data mining and simulations are used to identify root problems of a system (Brailsford, 2007; Koh & Tan, 2005). More sophisticated methods provide more information and may provide better results than simple methods; however, they are more time and resource intensive and may require specially trained consultants or researchers to perform.

After the qualities and root problems of a system have been investigated, strategic changes to the system are determined to fix the problems and improve the qualities. In some situations, it may be wise to simulate the changes to a system before they are

implemented. Simulations can be used to determine the effectiveness of any system change or to search for unintended consequences. Using simulations in healthcare is beneficial since lives are at risk. Overall, testing process improvements using simulations reduces risk and aids decision making.

Simulation in Healthcare

In healthcare, simulations are often used as disease, operational, or strategic models (Brailsford, 2007). Disease models involve the human body, operational models involve medical units (usually including patients), and strategic models are high level analyses (usually not including individual patients) (Brailsford, 2007). Each of these different uses can be performed by a number of different computer simulation methods. An evaluation of literature finds that the three most common computer simulations used in healthcare are discrete-event simulations (DES), Monte Carlo simulations, and system dynamics (Brailsford, 2007; Mustafee, Katsaliaki, & Taylor, 2010). DES are stochastic, dynamic, and discrete simulations meaning that some variables are random, changes in time are important, and the events in the model occur at discrete instances (Park & Leemis, 1999). DES simulations are often used as operational models because they are suited for decision makers who are evaluating the efficiency of current systems, improving systems, or planning for new systems (Mustafee et al., 2010). Like DES, Monte Carlo simulations are also stochastic; however, they are static meaning that changes in time are not important (Park & Leemis, 1999). Monte Carlo simulations are mainly used as disease or operational models because they are useful in health economics and the evaluation of different healthcare interventions (Mustafee et al., 2010). System

dynamics are dynamic, continuous simulations which focus on how the parts of a system interact with each other over time using feedback loops (Forrester, 1997). System dynamics are mainly used as strategic models because they are good for top-level evaluations involving policies or public health (Mustafee et al., 2010).

Of the three common healthcare model types, DES models are the most suited towards unit-level process improvements which is the primary focus of this research. The next section provides a more detailed explanation of DES models, and how they have been specifically used in healthcare.

Discrete-Event Simulation in Healthcare

DES is one of the most widely used operations researcher methods. It has been used in many industries including logistics (Tako & Robinson, 2012), defense (Hill, Miller, & McIntyre, 2001), and healthcare (Gunal & Pidd, 2010). In healthcare, DES models usually evaluate metrics like wait times (Duguay & Chetouane, 2007), throughput (Ferrin et al., 2007), and length of stay (Komashie & Mousavi, 2005). Popular units to model include emergency units and inpatient units; there are few whole-hospital model (Gunal & Pidd, 2010).

DES model use entities with attributes which pass through a network of activities, much like patients in a medical unit, making them a natural fit. Additionally, they have the usual benefits that come with simulations. Namely, they are a timely and cost effective method of evaluating current and future systems. Doing so improves understanding and can reduce decision making risks. Compared to other operations

research methods, DES models require fewer assumptions, are more realistic, and have results which are easier to communicate to stakeholders (Davies & Davies, 1994).

There are a few limitations to consider regarding DES models. One limitation is that DES models require large amounts of data to construct (Brailsford, 2007). Data requirements have historically limited the size and detail of most DES models. Fortunately, hospitals have been shifting towards the use of electronic patient record systems, which automatically generate data that can be used to help build DES models. A second limitation with DES models is that they usually lack generalizability (Brailsford, 2007; Gunal & Pidd, 2010). The results that DES models provide are useful for the particular system that they model, but they usually cannot be applied to other units or hospitals. However, the methods of modeling a unit can be used as templates to help build future models of other units.

Modeling Mental Workload

When evaluating systems using simulations, it can be easy to focus on physical resources and constraints and neglect the human element of the system. The human element, particularly mental workload, can be critical or even the limiting factor of a system. For the context of this thesis, mental workload is the amount of work being performed by an individual at a given moment in time. The mental workload of workers in a system is important because it plays a significant role in human performance. The non-linear relationship between human performance and mental workload is described by the Hebb-Yerkes-Dodson law which describes how the relationship between workload

and human performance is an inverted-U: performance is poor during both low and high workload levels (Teigen, 1994; Yerkes & Dodson, 1908).

Low performance due to high workload levels can be seen in past studies on real-world medical systems. In 2007, Weissman et al. compared hospital data on adverse event rates and workload; the research yielded results indicating hospitals which are at or over capacity may have higher rates of patient safety events (Weissman et al., 2007). Gurses, Carayon, and Wall evaluated workload by focusing on work obstacles. This study found that performance obstacles can lead to increased staff workload which leads to a decrease in perceived safety of care (Gurses, Carayon, & Wall, 2009). The researchers could not find studies evaluating the effect of low workload on performance in real-world medical systems. The lack of studies evaluating human performance at low workloads is likely due to high workload demands being more noticeable and concerning than low workloads. While this is a research gap, it will not be addressed as part of this research.

The support of theoretical and applied research on the topic of mental workload and performance suggests that process improvements should have a greater focus on workload. One of the main challenges is the ability of researchers to accurately model workload. Despite the evidence that workload is related to human performance, there are few process improvement tools which quantitatively model mental workload. The United States Army Research Laboratory has recognized the importance of evaluating the human element of a system by funding the development of a software tool called the Improved Performance Research Integration Tool (IMPRINT), which uses discrete-event simulation to model human performance (Mitchell, 2000). IMPRINT has many of the

same attributes of traditional DES methods. The distinguishing difference is its ability to model the mental workload of human agents in a system.

IMPRINT quantifies mental workload over time using the visual, auditory, cognitive, and psychomotor (VACP) method which is based on the work of McCracken and Aldrich and Bierbaum, et al (Bierbaum, Szabo, & Aldrich, 1989; McCracken & Aldrich, 1984). The VACP workload methodology uses multiple resource theory to divide mental resources into visual, auditory, cognitive, fine motor, gross motor, speech, and tactile channels. The standardize VACP values used in IMPRINT are shown in Appendix A – VACP Tables. The IMPRINT workload outputs include level, duration, timing, and tasks responsible for the workload experienced by a worker. The outputs can be analyzed qualitatively or quantitatively. For example, workload values can be compared to a threshold indicating when a worker is overloaded. Alternatively, workload outputs for different models could be statistically compared to evaluate the workload impacts of system changes.

Like other simulation tools, a limitation of IMPRINT is the data needed to build models. The data requirements increase significantly as the size and complexity of the system being modeled increases. Unfortunately, a typical manager would struggle to use IMPRINT unless they received months of training. The use of IMPRINT on a wide-scale will require specially trained researchers or consultants.

Historically, IMPRINT has been primarily used to determine manpower requirements for military applications and research (Rusnock & Geiger, 2013). Additionally, there have been IMPRINT studies on the evaluation of mental workload differences between human-human teams versus human-robot teams (Harriott, Zhuang,

Adams, & Deloach, 2012) and the influence of adaptive automation on mental workload and situational awareness (Rusnock & Geiger, 2013). An exhaustive literature review was unable to find any use of IMPRINT in the healthcare industry, which is likely due to the limited availability of IMPRINT through the Army Research Laboratory.

Research Gap

When the qualities of a system are accurately defined and a thorough analysis has been performed, process improvements can be beneficial for the healthcare industry. While there are many different process improvement methods, many in the healthcare industry have neglected to consider mental workload – despite research showing a relationship between mental workload and human performance. The capabilities of IMPRINT to explicitly simulate the mental workload of workers in a system are unpreceded. This study aims to contribute to the body of knowledge by using IMPRINT in a novel way to quantitatively model the mental workload of workers in a healthcare system for the purposes of process improvement. While the IMPRINT simulation results of this research are only applicable to the modeled unit, the methods used are generalizable.

Summary

The literature presented in this chapter is important in developing an understanding of the topic and significance of the research gap. The healthcare industry is in need of improvements in efficiency and safety. Performing analyses of healthcare systems and determining the root causes of problems are useful in effectively improving processes. Analyses of medical staff mental workload in healthcare systems has been

sparse – despite research indicating the importance of workload on human performance. The goal of this research is to use IMPRINT to quantify the mental workload of staff in a hospital unit. Chapters III, IV, and V address the research gap and provide information for the 88th Medical Group for the purposes of process improvements.

III. Assessing Mental Workload Demands of Healthcare Staff using Simulation

Abstract

The United States healthcare system is being pressured by an aging population, retiring medical work force, and budget constraints. Each year, preventable medical errors cause hundreds of thousands of deaths in the United States. Many process improvement tools have been applied to the healthcare industry to improve safety and efficiency. However, nearly all of these tools have neglected to explicitly quantify mental workload of healthcare providers despite the consensus that it is related to human performance. This research effort uses the Improved Performance Research Integration Tool (IMPRINT), a discrete-event simulation (DES), to model human performance by quantifying mental workload. This tool has primarily been used to determine manpower and design requirements for military applications. This study takes a unique approach by using IMPRINT to quantitatively model the mental workload demands of healthcare workers. Specifically, this research examines nurses and technicians in an inpatient unit at the Wright-Patterson Medical Center to detect workload differences between staff and identify trends which lead to high workload demands.

Introduction

The aging United States population is beginning to challenge the national healthcare system. Colby and Ortman (2014) estimate that by 2030, 20% of Americans will be age 65 or older. The increase in senior citizens is significant because of their susceptibility to injuries and illnesses. Additionally, many healthcare providers are expected to retire, putting greater demands on the young workers who remain in the

profession (Center for Health Workforce Studies School of Public Health, 2006). Ultimately, these factors threaten to increase the workload of the providers who will be required to take on more work to keep the system running.

An increase in workload for healthcare providers is a concern because it may lower the quality of patient care. The relationship between workload and human performance can be shown with the Hebb-Yerkes-Dodson Law: high and low workloads result in lower human performance (Teigen, 1994; Yerkes & Dodson, 1908). This relationship has been supported in multiple healthcare studies. One study found that hospitals which are at or over capacity are more likely to have higher rates of patient safety events (Weissman et al., 2007). A second study illustrated how performance obstacles which lead to higher workloads may decrease the perceived safety of care for patients (Gurses et al., 2009). Human performance is already an issue for the U.S. healthcare system. Preventable medical errors cause an alarming number of deaths and injuries each year. One study estimated that 98,000 Americans died in 1984 from preventable medical errors (Kohn et al., 1999). A more recent study estimated that 400,000 Americans die each year from preventable medical errors and that there are 10-20 times as many non-fatal preventable medical errors (James, 2013).

Concerns with the U.S. healthcare system have sparked a number of healthcare process improvement studies. Many studies have used discrete-event simulations to model parts of hospitals, such as emergency and inpatient units (Gunal & Pidd, 2010). Discrete-event simulations are useful because they are predictive and have results which are easy to understand and communicate to others (Davies & Davies, 1994). Most discrete-event simulations, and other healthcare process improvement studies, focus on

throughput metrics like wait time and length of stay (Duguay & Chetouane, 2007; Ferrin et al., 2007; Komashie & Mousavi, 2005). Unfortunately, there is a lack of research evaluating healthcare systems by explicitly quantifying mental workload of healthcare staff.

The Improved Performance Research Integration Tool (IMPRINT), originally created for the Army Research Laboratory, is a unique discrete-event simulation software tool which models mental workload. It has primarily been used for military research and applications (Rusnock & Geiger, 2013). We could find no documented use of IMPRINT for modeling healthcare systems.

Research Objective

The projected increase in senior citizens and preventable medical errors creates a need for improvements to the U.S. healthcare system. Many process improvement studies have been performed on healthcare systems, but they have not specifically evaluated the effects of mental workload. The objective of this article is to address this gap by using IMPRINT in a novel way to quantitatively model the mental workload of healthcare staff. This research uses the mental workload outputs to evaluate workload differences between staff and identify trends which lead to higher mental workload.

Methodology

This research uses IMPRINT to model the mental workload of healthcare staff in the Medical Surgical Unit (MSU) at the Wright-Patterson Medical Center. The MSU is a 39-bed, inpatient unit for stable patients who are usually recovering after a surgery or Emergency Room visit. The average length of stay for a patient is 2.4 days. Patients

receive most of their hands-on-care from nurses and technicians. The MSU staffing levels remain nearly constant over time. Staff members work 12-hour shifts which change at 06:00 and 18:00. There are normally 12 staff members in the MSU at one time: 6 nurses, 4 technicians, 1 charge nurse, and 1 shift leader on duty. The charge nurse is a nurse leadership position that supervises the entire unit and assigns patients to nurses and rooms. The shift leader is a technician leadership position that manages all technicians and assigns patients to technicians, in addition to caring for patients. The IMPRINT model for this research simulates the mental workload of these 12 staff members over 1 week in the MSU. The model uses a 2-week warmup period to populate the model with patients and reach a steady state. Physicians are not included in the model because they are not explicitly assigned to the MSU.

Model Creation

Interactions with healthcare staff and patient records were required to build an IMPRINT model, thus initiating an Institutional Review Board (IRB) review. The signed IRB exemption letter is located in Appendix B – IRB Letters. Appendix B – IRB Letters also includes the informed consent document which was signed by the staff who participated in this research. Careful steps were taken to protect the healthcare staff and patient records.

To build a conceptual model of the workflow in the MSU, the researchers performed the following task analyses on the MSU staff: 6 general interviews, 4 hours of direct observation, 2 simulation interviews, and 2 verbal protocol task analyses. Additionally, the researchers used documents produced by the MSU staff such as staffing schedules and employee checklists. The researchers used the conceptual model to build

an IMPRINT task network which includes the main tasks, flows, and logic of the MSU. The task network was verified by 6 Subject Matter Experts (SME) which included 2 charge nurses, 2 nurses, and 2 shift leaders.

The key components of the IMPRINT task network are shown in Figure 1. Rounded boxes are task nodes. Purple nodes are system tasks, yellow nodes are charge nurse tasks, orange nodes are shift leader tasks, blue nodes are nurse tasks, and green nodes are technician tasks. Square boxes are functions with task networks embedded inside them. For example, the task network in Figure 2 is contained in the function 70 and the task network in Figure 3 is contained in the function 77. In total, the model uses 685 task nodes to represent the workflow of the MSU. For this model, the duration of each run is determined by a timer which runs the model for three simulation weeks. The first two weeks are used to reach a steady state and the third week is used to evaluate the system. The arrival rates of patients in the model are based on the day of the week and the time of the day. If the MSU has an open room, new patients are assigned to a nurse and a technician. When a new patient enters the system, the nurse caring for the least number of patients at that moment is assigned the new patient. If there is a tie, the lowest numbered nurse in the IMPRINT model has priority. The same logic is used with the technicians. The only difference is that the shift leader is a special type of technician who has other responsibilities besides caring for patients, so all other technicians must be assigned at least 1 more patient than the shift leader before the shift leader receives a patient. The assignment logic was created to be as balanced and realistic as possible. Nurse1 and technician1, seen in Figure 1, are analogous to the most experienced staff members and are thus assigned more patients because of their experience and track

record. However, it is important to note that all nurses and technicians have identical experience levels in the IMPRINT model. For their respectively assigned patients, the nurses perform the tasks in Figure 2 and the technicians perform the tasks in Figure 3. The duration that a patient is in the model is determined by using a length of stay distribution built from the real-world MSU records. The model discharges the patient after their length of stay duration is completed. After a 72-hour delay, the charge nurse performs a callback and the patient is completely removed from the task network. The full logic of the task network is included in Appendix D – Baseline Model.

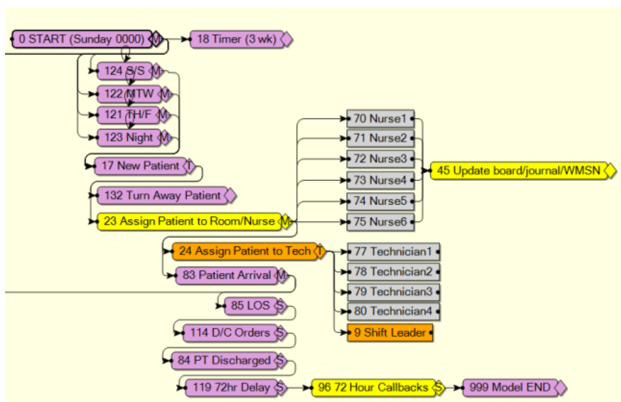

Figure 1: Section of Network Diagram

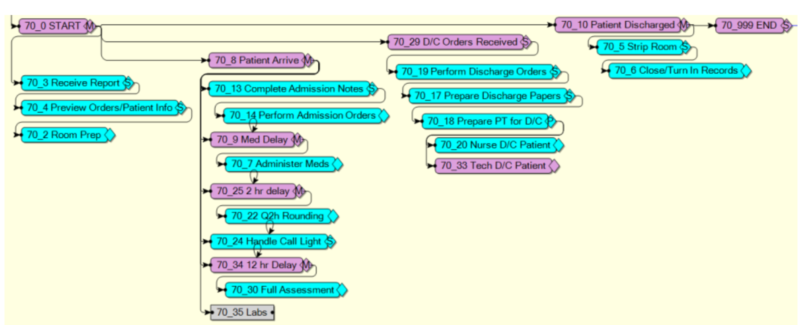

Figure 2: Nurse Function

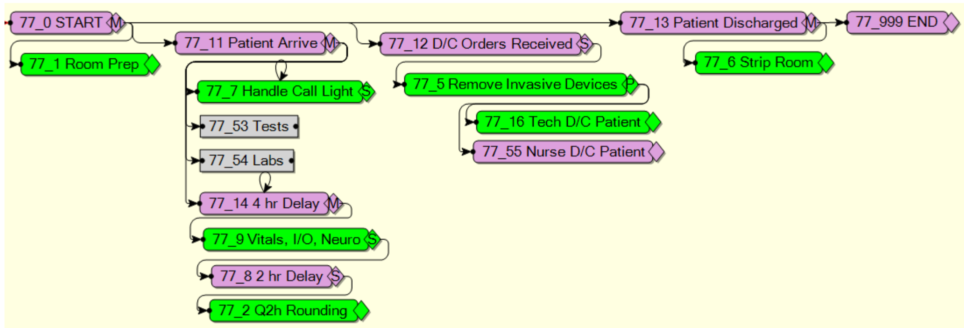

Figure 3: Technician Function

The task network required 61 metrics, including probabilities, arrival rates, and task durations, to accurately represent the real-world MSU. These data requirements were fulfilled using 1 month of Essentris patient records and information obtained from the 6 SMEs. Essentris is the electronic medical record system used in the MSU. The Essentris records were used to determine the distribution of patient length of stay and the arrival rate of patients based on the day of the week and the time of day. The length of stay metric was fit to a lognormal distribution and triangular distributions were used for the patient arrival rates. SME estimates were used for the remaining data requirements (i.e., individual process times). Each SME was asked to provide a minimum, mode, and maximum estimate for each metric which were used to create triangular distributions. To ensure that variability was being captured, the SME triangular distributions use the extreme minimum and extreme maximum of each SME and the average of the modes.

Each IMPRINT task which is performed by the MSU staff requires a visual, auditory, cognitive, and psychomotor (VACP) workload value so that IMPRINT can determine the workload of each member over time. The VACP method represents the

workload of a task by using multiple resource theory which divides the mental resources of a worker into the following seven channels: visual, auditory, cognitive, fine motor, gross motor, speech, and tactile. The workload demand of each channel is determined using a scale from 0 to 7. The VACP scales include text descriptions for each value to help make appropriate selections, and are based on the work of McCracken and Aldrich (McCracken & Aldrich, 1984) and Bierbaum, et al (Bierbaum et al., 1989). Tables which include the VACP scales and text descriptions are included in Appendix A – VACP Tables. IMPRINT sums all VACP values across each channel for each task to create a task total. At each instance in time during a model run, the task totals for all tasks being performed at that instance for each worker are summed to create a single VACP value for each worker at each point in time, creating a workload profile that captures the variation in workload over time.

Model Validation

The MSU IMPRINT model was validated using 4 emergent behavior metrics: weekly discharge, bed utilization, idle time, and task workload demands. Weekly discharge is the number of patients discharged from the MSU in one week. Bed utilization is the number of patients in the MSU at the end of each day at midnight. Idle time is the percentage of time in a week that each staff member is available to work but at zero workload. Task workload demand is the rank order of the mental demand, or VACP value, of each task. Validating weekly discharge and bed utilization ensures that the model accurately represents the real-world patient throughput of the MSU. Validating idle time and task workload demands ensures that the model accurately represent the real-world workload demands placed on the MSU staff. The model's weekly discharge metric

was successfully validated against 2 years of MSU records using a two-sample T-test (n=104, P-value=0.928). As shown in Table 1, the 95% confidence interval for the weekly discharge was 41% smaller than the 2 years of MSU records meaning that the model has less weekly discharge variability than the real-world. The model's bed utilization metric was successfully validated against 1 month of Essentris records using a two-sample T-test (n=28, P-value=0.891). As shown in Table 1, the 95% confidence interval for the model bed utilization was 15% larger than the Essentris records meaning the model has slightly more bed utilization variability than the real-world.

Table 1: Weekly Discharge and Bed Utilization Validation

Weekly Discharge	**MSU Records 95% CI**	50.625	54.990
	IMPRINT 95% CI	51.625	54.222
	P-Value	0.928	
Bed Utilization	**MSU Records 95% CI**	18.836	22.307
	IMPRINT 95% CI	18.390	22.396
	P-Value	0.891	

The model's idle time metric was successfully validated using SME estimates of idle time. Four SMEs (2 nurses and 2 technicians) were asked to provide 95% confidence intervals for the amount of idle time that they experience in a week. The confidence intervals were averaged for the nurses and technicians. The IMPRINT confidence intervals were created from the idle time outputs for 10 models runs (nurse n=60, technician n=40). As Table 2 shows, the confidence intervals overlap so there are no significant differences. See Appendix F – Baseline Model Validation for the complete set of idle time validation data. Task workload demand was validated by asking 4 SMEs

(2 nurses and 2 technicians) to rank order the main tasks they perform in the MSU. The ranks for the two nurses and two technicians were averaged and compared with the VACP values for the tasks in IMPRINT as shown in Table 3 and Table 4. The VACP values are based on task complexity and are consistent with the SME estimates.

Table 2: Nurse Idle Time Validation

	SME 95% CI		IMPRINT 95% CI	
Nurses	24.2%	48.6%	42.1%	47.0%
Technicians	35.2%	55.2%	49.8%	53.9%

Table 3: Nurse Task Workload Demand Validation

Nurse Main Tasks	Subject 11	Subject 9	Average	Workload Category	IMPRINT VACP
Performing Admission Orders	1	1	1	High	23.6
Administering Medication	3	2	2.5	High	22.6
Full Assessment	5	3	4	High	22.6
Handling Call Light	2	7	4.5	Medium	20.8
Q2h Rounding	4	6	5	Medium	16.8
Receiving Report	7	4	5.5	Medium	16.5
Collecting Labs	6	5	5.5	Medium	14.6
Preparing Room	9	8	8.5	Low	9.2
Stripping Room	8	9	8.5	Low	8.8

Table 4: Technician Task Workload Demand Validation

Technician Main Tasks	Subject 10	Subject 8	Average	Workload Category	IMPRINT VACP
Handling Call Light	1	1	1	High	20.8
Vitals, I/O, Neuro	4	3	3.5	High	19.2
Q2h Rounding	2	6	4	Medium	16.8
Collecting Labs	3	7	5	Medium	14.6
Transporting PT to Test	6	4	5	Medium	10.2
Preparing Room	8	2	5	Medium	9.2
Stripping Room	7	5	6	Low	8.8
Removing Invasive Devices	5	8	6.5	Low	7.2

Overload Threshold

This research uses IMPRINT to determine when a staff member is overloaded which is defined as the times a worker is behind on tasks, task performance is suffering, and the worker is losing track of the "big picture." An overload threshold is needed to determine the VACP value at which each staff member is overloaded. For this research, the overload threshold was determined by asking 2 SMEs (1 nurse and 1 technician) to provide 95% confidence intervals for the percentage of a week they feel overloaded (shown in the first row of Table 5). The SMEs provided estimates in terms of hours-per-week. The researchers converted the estimates from hours-per-week to percent-of-week which resulted in the decimal estimates shown in Table 5. The SME estimates were compared with the 95% confidence intervals of the percentage of time that nurses and technicians are above 4 different VACP values for 60 IMPRINT runs. As Table 5 shows, the VACP value of 35 provides the best fitting overlap with the SME estimates because it falls within the SME confidence intervals for both nurses and technicians. The confidence intervals of the SME estimates are much larger than the IMPRINT outputs. The researchers believe that the difference in variability is primarily due to a lack of confidence of the SMEs. Ultimately, this is a limitation of this research. It may be beneficial to gather more SME estimates in order to reduce the width of the real-world overload time confidence intervals.

Table 5: Overload Confidence Intervals (60 runs)

	Nurse Overload 95% Confidence Interval		Tech Overload 95% Confidence Interval	
SME	2.08%	6.25%	3.47%	9.03%
30 VACP	5.93%	6.27%	6.06%	6.82%
35 VACP	4.71%	4.98%	5.12%	5.81%
40 VACP	3.48%	3.69%	2.56%	2.95%
45 VACP	2.64%	2.84%	0.75%	0.93%

Variables and Model Replications

For this research, the independent variable is staff type and dependent variables include idle time; average workload; overload percent; overload instances; cumulative time spent on each task; and cumulative time spent on each task while overloaded. Idle time occurs when a staff member experiences zero VACP workload and is found by adding all of the idle time a worker experiences in one week and dividing that value by the time in a week. The average workload is the time weighted average of the VACP workload of a staff member over one week. The overload percent is found by adding all of the times when a staff member is overloaded and dividing that value by the time in a week. Overload instances are the number of times in a week that a staff member is overloaded. The total time spent on each task is found by adding all of the times in a week that a staff member is performing a specific task. Similarly, the time spent on each task while overloaded is found by adding all of the times in a week that a staff member is performing a specific task while overloaded.

To properly evaluate the workload metrics, the IMPRINT model was run 60 times. The required number of runs was determined using the half-width of the weekly discharge metric since it is an important metric in determining the workload of the

healthcare staff. The weekly discharge metric of the MSU records has a half-width (h) of 2.18. An initial 10 replications (n0) of the IMPRINT model yielded an initial weekly discharge half-width (h0) of 5.28. Using Equation 1, the IMPRINT model needs n = 58.6 runs to reach this half-width. For this reason, 60 runs were performed. The idle time, average workload, overload percent, and overload instances data are from the 60 model runs. However, only 10 of the 60 runs were used to create the two task time metrics shown in Table 11 due to the intensive post-processing needed.

$$\boldsymbol{n = n_0 \frac{h_0^2}{h^2}} \qquad \textbf{(1)}$$

Analysis and Results

On average, nurse1 and technician1 experience the least idle time, highest average workload, highest overload time, and the most overload instances compared to their fellow nurses and technicians. These results were expected because of the assignment logic explained in the methodology section. Paired T-tests were performed to evaluate the statistical significance of the staff differences. Paired T-tests were used, as opposed to two-sample T-tests, to reduce the unnecessary variability that occurs due to different patient loads in different runs. The complete set of p-values is shown in Tables 7-10. Note that highlighted values are statistically significant. For idle time and average workload, nurse1 is statistically different than the other nurses at a p-value less than 0.001. However, for overload percent, nurse1 is not statistically different than nurse2 (p-value = 0.212), nurse3 (p-value = 0.094), or nurse5 (p-value = 0.073). Also, for overload instances, nurse1 is not statistically different than nurse5 (p-value = 0.057). Therefore,

nurse1 has the most extreme values for idle time and average workload. Nurse1 also has an equal or greater overload percent and number of overload instances than all of the other nurses. Technician1 is statistically different than all of the technicians at a p-value of 0.035 or less for all 4 workload metrics. Given these results, it is conservative to focus on nurse1 and technician1 as representative of all nurses and technicians because they are the first of their staff types to experience workload issues.

Table 6: IMPRINT Workload Outputs (60 runs)

	Percent of Idle Time in One Week		Average Workload over One Week		Percent of Week Overloaded		Number of Overloaded Instances in One Week	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
Nurse1	36.76%	8.73%	13.26	1.78	5.14%	0.93%	63.13	11.89
Nurse2	39.48%	8.54%	12.61	1.73	4.93%	0.98%	58.18	13.33
Nurse3	41.51%	8.55%	12.23	1.78	4.89%	0.91%	59.10	10.82
Nurse4	43.79%	7.93%	11.73	1.61	4.75%	0.89%	56.77	11.47
Nurse5	46.77%	8.09%	11.21	1.72	4.87%	0.84%	59.17	12.97
Nurse6	48.94%	7.80%	10.68	1.65	4.50%	0.88%	53.95	12.99
Technician1	48.32%	6.00%	10.70	1.60	6.08%	1.98%	127.33	48.10
Technician2	50.48%	5.81%	10.22	1.48	5.74%	1.82%	118.08	40.75
Technician3	51.88%	6.40%	9.78	1.59	5.19%	1.73%	102.27	36.98
Technician4	53.47%	6.45%	9.42	1.63	4.85%	1.82%	98.85	41.33
Charge Nurse	47.48%	1.47%	9.03	0.39	2.07%	0.32%	91.25	16.45
Shift Leader	55.05%	6.37%	8.48	1.51	3.28%	1.38%	73.00	31.91
***Average Weekly Discharge for the 60 runs was 52.68 patients.**								

Table 7: Idle Time Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.000											
Nurse3	0.000	0.001										
Nurse4	0.000	0.000	0.000									
Nurse5	0.000	0.000	0.000	0.000								
Nurse6	0.000	0.000	0.000	0.000	0.000							
Technician1	0.000	0.000	0.000	0.000	0.008	0.308						
Technician2	0.000	0.000	0.000	0.000	0.000	0.006	0.000					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002			
Charge Nurse	0.000	0.000	0.000	0.000	0.454	0.109	0.216	0.000	0.000	0.000		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	

Table 8: Average Workload Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.000											
Nurse3	0.000	0.001										
Nurse4	0.000	0.000	0.000									
Nurse5	0.000	0.000	0.000	0.000								
Nurse6	0.000	0.000	0.000	0.000	0.000							
Technician1	0.000	0.000	0.000	0.000	0.000	0.810						
Technician2	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.036		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	

Table 9: Overload Percent Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.212											
Nurse3	0.094	0.821										
Nurse4	0.015	0.309	0.375									
Nurse5	0.073	0.716	0.867	0.365								
Nurse6	0.000	0.007	0.013	0.077	0.011							
Technician1	0.000	0.000	0.000	0.000	0.000	0.000						
Technician2	0.016	0.001	0.000	0.000	0.000	0.000	0.035					
Technician3	0.828	0.252	0.203	0.045	0.101	0.002	0.000	0.001				
Technician4	0.244	0.760	0.859	0.644	0.936	0.083	0.000	0.000	0.039			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Table 10: Overload Instances Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.031											
Nurse3	0.036	0.627										
Nurse4	0.002	0.518	0.203									
Nurse5	0.057	0.663	0.972	0.188								
Nurse6	0.000	0.046	0.008	0.162	0.008							
Technician1	0.000	0.000	0.000	0.000	0.000	0.000						
Technician2	0.000	0.000	0.000	0.000	0.000	0.000	0.023					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.347			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.013	0.099		
Shift Leader	0.009	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Each of the workload metrics in Table 6 vary between the different staff types. Despite the variation, each staff type experiences high amounts of idle time. An interesting result is that the technicians have the highest percentage of overload time and overload instances compared to the other staff types, despite the nurses having higher

average workloads and less idle time. This is because technicians mostly perform many quick, unplanned tasks like “Handling Call Lights” while nurses mostly perform slow, planned tasks like “Full Assessments.”

Table 11 shows the most time consuming and overloading tasks for the different staff types. First, the model indicates that nurses spend the most time on “Q2h Rounding” which involves checking on each patient every 2 hours to see if they are having any issues or need any help. Technicians and the shift leader spend the most time on “Q2h Rounding” and “Vitals, I/O, Neuro.” “Vitals, I/O, Neuro” involves checking the patients vital signs, food intake, bowel movements, and sensory responses. The charge nurse spends the most time helping visitors and answering phone calls. Next, the model predicts that nurses spend the most overload time when administering medication. Technicians and the shift leader spend the most overload time during “Vitals, I/O, Neuro.” The charge nurse has the most overloaded time when assigning patients to a room and nurse. Finally, using the total and overload time for each task, a percentage of time that each task is performed while overloaded is found. For the nurses, performing discharge orders has the highest overload percentage. Technicians and the shift leader have the highest overload percentage on “Vitals, I/O, Neuro.” The charge nurse has the highest overload percentage while attending the daily bed meeting.

Table 11: IMPRINT Task Time Outputs (10 runs)

Nurse 1				Shift Leader			
Task	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Task	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Administer Meds	5.21	15.05	37%	Assign Patient to Tech	0.88	4.36	20%
Close/Turn In Records	0.09	1.36	6%	Handle Call Light	3.80	14.78	25%
Complete Admission Notes	0.13	2.39	5%	Misc Cleaning	0.07	6.12	1%
Full Assessment	4.56	13.82	35%	Q2h Rounding	1.81	20.90	8%
Handle Call Light	1.94	7.71	24%	Remove Invasive Devices	0.04	0.80	5%
Nurse 1 Shift Change	0.15	7.61	2%	Restock PT & Supply Rooms	0.11	6.00	2%
Collect Labs	0.07	2.54	3%	Retreive from Test	0.12	2.66	4%
Nurse D/C Patient	0.05	0.95	5%	Room Prep	0.05	0.70	6%
Perform Admission Orders	1.35	6.90	18%	Shift Ldr Misc Checks	0.31	4.06	8%
Perform Discharge Orders	0.62	1.59	39%	Shift Ldr Shift Change	0.24	4.46	5%
Prepare Discharge Papers	0.31	1.15	29%	Strip Room	0.04	1.08	4%
Prepare PT for D/C	0.37	1.70	22%	Collect Lab	0.15	3.54	4%
Preview Orders/Patient Info	0.01	0.75	2%	Tech D/C Patient	0.04	1.14	4%
Q2h Rounding	3.28	53.07	6%	Tech, Q Sunday Night Tasks	0.00	0.46	0%
Receive Report	0.20	1.78	11%	Transport to Test	0.20	2.65	7%
Room Prep	0.03	0.90	2%	Vitals, I/O, Neuro	5.70	20.85	27%
Strip Room	0.03	1.32	2%				
Technician 1				**Charge Nurse**			
Task	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Task	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Handle Call Light	6.33	20.03	30%	72 Hour Callbacks	0.24	5.78	4%
Q2h Rounding	3.85	30.81	12%	Assign Patient to Room/Nurse	3.32	9.96	33%
Remove Invasive Devices	0.09	1.20	6%	Bed Meeting (0745, M-F)	0.53	1.39	38%
Retreive from Test	0.30	3.86	7%	Charge Rounds	1.32	16.56	8%
Room Prep	0.10	1.17	8%	Clean Nurse Station (0715/1915)	0.05	2.27	2%
Strip Room	0.13	1.70	8%	CN Shift Change	0.27	8.19	3%
Tech 1 Shift Change	0.02	2.22	1%	Handle Call Light	0.59	5.61	10%
Collect Lab	0.48	6.05	8%	Help Visitors/Phone Calls	2.77	48.09	6%
Tech D/C Patient	0.14	1.71	7%	Internal Med Meeting (830, M-F)	0.77	3.32	23%
Transport to Test	0.40	3.72	9%	Nurse, Q Sunday Night Tasks	0.01	0.80	2%
Vitals, I/O, Neuro	11.33	31.25	35%	Restock Med Room	0.11	3.08	4%
				Update board/journal/WMSN	0.15	10.07	2%

Discussion

The 88th Medical Group MSU is a high performing unit with few medical errors. Yet, improvements could be made by reducing the amount of overload time for the medical staff. Reducing task durations with improvements in efficiency would probably have minor effects on overload since the staff overload is not due to shortage of time (some idle time exists) but rather the staff is experiencing a combination of high workload tasks simultaneously. The results suggest three ways to reduce overload: workload balancing, task complexity reduction, and task urgency management.

Balancing workload may be useful because of the excess idle time that each worker experiences in a week and the differences in workload between staff members. One way to balance workload is by using idle time to work ahead on tasks. In the real-

world, workers have their own way of managing time; some work ahead and some procrastinate. This IMPRINT model does not allow for working ahead. Working ahead should reduce the amount of multitasking which needs to be performed which would reduce overload. Besides working ahead, workload can be balanced between staff members. Currently, the model balances patient assignments but it does not allow for dynamic task balancing. In reality, the staff shares some of their work to help balance the workload. Allowing for some tasks to be shared and encouraging workload balancing could reduce many instances of overload. However, only some tasks can be shared because many tasks require special qualifications and carry liability concerns. Also, balancing workload becomes less useful during times when all staff members are experiencing high workload levels.

Besides workload balancing, overload could be reduced by decreasing task complexity. The tasks with the highest overload percent in Table 11 are also some of the most complex tasks. For example, performing “Discharge Orders” (VACP value = 23.6), “Full Assessments” (VACP value = 22.6), and “Administering Medication” (VACP value = 22.6) have the highest overload percent and highest task complexity for nurses. High complexity tasks have high overload percentages because the staff member becomes overworked the instant that any other task arises, assuming that multitasking is allowed. Evaluating the specific VACP channels for “Discharge Order”, the cognitive, fine motor, and speech channels make up most of the workload. Focusing on ways to reduce the workload in these channels for this specific task could reduce the overload experienced during this task. For example, the cognitive channel may be reduced by implementing a discharge order checklist which may lower the cognitive demands of the

task. The other high overload percent tasks could be evaluated in the same way as a targeted effort to reduce workload.

This study suggests task urgency management as a final method to reduce overload. When coupled with high complexity tasks, task urgency can lead to more extreme overloading. For example, the "Admission Orders" and "Discharge Orders" tasks have the same task complexity (VACP value = 23.6); however, "Admission Orders" is performed while overloaded 18% of the time compared to 39% of the time for "Discharge Orders." This dissimilarity is due to a difference in urgency between the two tasks. In the MSU, the "Admission Orders" task starts when the assigned nurse is not performing any other tasks because it is not time critical. On the other hand, "Discharge Orders" need to be addressed quickly to make space for other patients and keep the patient length of stay to a minimum. The model represents this urgency by starting "Discharge Orders" the moment that they are received. For this research, task urgency management involves making strategic changes to the workflow logic which decides when a task is initiated. Reducing the urgency of tasks could reduce the need for multitasking and the amount of overload; but, this could come at the cost. In the "Discharge Order" example, reducing urgency would mean that the patient would not be discharged as quickly, thus resulting in less room for new patients, while also increasing the patient length of stay. Less room in the MSU could have cascading effects by slowing the transfer of patients from the Emergency Room, which would also increase their length of stay in the Emergency Room.

Conclusion

Using IMPRINT to model the healthcare systems is a useful way to quantify the mental workload of healthcare staff. Many different types of workload metrics can be generated to evaluate differences between staff and provide insights into why overloading occurs and how it could be reduced. The results of this research suggest the 88th Medical Group MSU could benefit from workload balancing, reduced task complexity, and task urgency management. The results are specific for the 88th Medical Group MSU and may not be generalizable for other units. However, the methodology of using IMPRINT workload modeling to identify sources of workload demand is generalizable.

The researchers plan to expand on this research by creating alternate models to test the influence of patient load on mental workload by incrementally increasing the patient load. Additionally, different workload balancing schemes will be implemented and tested in the model to investigate the potential benefits of such strategies. There are a number of other useful ways IMPRINT could be used to evaluate healthcare systems. For example, the current IMPRINT outputs could be analyzed with a focus on time by comparing the workload metrics over the time in a day or days of the week. Additionally, alternate models could be created to study the effects of task complexity reduction and urgency management which were discussed in this paper.

IV. Simulation-Based Evaluation of the Effects of Patient Load on Mental Workload of Medical Staff

Abstract

In Ohio, Veterans Affairs (VA) Medical Centers are working to handle patient load issues by sending patient overflows to the Wright-Patterson Medical Center. The Wright-Patterson Medical Center will benefit from the increase in patients; however, there are concerns that the quality of patient care may suffer. If the increase in patients results in the medical staff experiencing high mental workload levels, human performance could be reduced. The objective of this research is to evaluate the influence of patient load on the mental workload of staff in an inpatient unit at the Wright-Patterson Medical Center. This objective is achieved using Improved Performance Research Integration Tool (IMPRINT), a discrete-event simulation tool. The results of this research find a linear relationship between patient load and workload metrics. Nurses and technicians experience the greatest negative impacts to mental workload as patient load increases.

Introduction

The Veterans Affairs (VA) Medical Centers around the United States are struggling to handle their patient loads which is resulting in wait time issues. In a report from late 2014, 600,000 VA patients seeking medical care were required to wait more than a month to be seen (Hoyer & Brook, 2014). VA Medical Centers are seeking ways to improve their wait times. In parts of Ohio, VAs are working to reduce wait times with a program called the Buckeye Federal Healthcare Consortium. This five-year consortium

allows some VA patients to receive care at the Wright-Patterson Air Force Base Medical Center (Barber, 2015). The consortium benefits the VA by reducing patient demands to improve wait times. Wright-Patterson Medical Center benefits by increasing its utilization which improves funding and gives military medical providers more experience.

Despite having many benefits, there are concerns that the consortium may reduce the quality of patient care at the Wright-Patterson Medical Center due to the new patient load. The consortium is expected to increase patient load of inpatient units by 30% to and outpatient clinics by 20-25% (Mort, 2015). If the medical center management team had a specific understanding of how the new patient load will affect its medical staff and patients, they could proactively prepare by making process improvement or policy changes.

In general, the MSU is expecting the increases in patient load to increase medical staff mental workload. Also, high patient loads would likely reduce patient care due to the Hebb-Yerkes-Dodson Law which shows how human performance is poor at low and high workloads (Teigen, 1994). This relationship has been empirically demonstrated, at the high workload end of the spectrum, by evaluating a hospital's capacity and occurrence rate of patient safety events (Weissman et al., 2007). While this general understanding is important, a more detailed analysis would be more useful for planning and process improvement purposes. Fortunately, mental workload can be quantitatively modeled using IMPRINT, a discrete-event simulation (DES) tool. This tool can be used to evaluate the mental workload of workers in both current systems and future systems.

The objective of this research is to evaluate the influence of patient load on the mental workload of staff in an inpatient unit in the Wright-Patterson Medical Center for the purposes of process improvement. The independent variable for this research is patient load and the dependent variables are idle time, average mental workload, overload time, total task times, and overload task times. The researchers use the Improved Performance Research Integration Tool, (IMPRINT) to answer the following three questions.

1. What is the relationship between patient load and medical staff mental workload metrics (idle time, average mental workload, overload time)?
2. Which medical staff workers experience the greatest negative impact in mental workload metrics as patient load increases?
3. How does patient load influence individual task performance (total task times and overload task times)?

Methodology

The researchers modeled the Medical Surgical Unit (MSU), an inpatient unit in the Wright Patterson Medical Center, which primarily cares for patients who are recovering from an Emergency Room visit or surgery. The average length of stay for patients is 2.4 days. The unit has 39 beds and normally staffs 6 nurses, 4 technicians, 1 charge nurse, and 1 shift leader at a time. The charge nurse is a type of nurse who manages the medical staff and makes patient assignments; they do not explicitly care for any patients. The shift leader is a technician who has special leadership duties in addition to caring for some patients. Physicians are not exclusively assigned to the MSU so they

are not include in the models. The IMPRINT model evaluates the mental workload of the 12 medical staff in the MSU over 1 week. It uses a 2-week warmup time to reach a steady state.

After gaining IRB approval, the researchers performed task analyses on the medical staff in the MSU to build a task network which can be seen in Appendix B – IRB Letters. The task network required data including arrival rates, probabilities, and task durations which were collected from MSU and electronic records and Subject Matter Experts (SME). The complete set of input data is included in Appendix C – Input Data Modeling. The workload value of each task is represented using the visual, auditory, cognitive, and psychomotor (VACP) workload methodology which is based on the work of McCracken and Aldrich (1984) and Bierbaum, et al (1989). It uses multiple resource theory by dividing mental resources into visual, auditory, cognitive, fine motor, gross motor, speech, and tactile channels. The researchers used the standardized VACP tables shown in Appendix A – VACP Tables.

Validation and Overload Threshold

The baseline model was validated using 4 emergent behavior metric included weekly discharge, bed utilization, idle time, and task workload demands. The model weekly discharge was validated by comparing IMPRINT outputs with MSU records using a two-sample T-test (n=104, P-value=0.928). The model bed utilization was validated by comparing IMPRINT outputs with Essentris Records using a two-sample T-test (n=28, P-value=0.891). Idle time was validated by comparing SME estimates of idle time to the idle times of 10 IMPRINT runs. Task workload demands were validated by comparing the SME rank order of task complexity to the VACP value of the IMPRINT

tasks. Specific information on the model validation are included in Appendix F – Baseline Model Validation. Ultimately, the model was successfully validated.

In order to evaluate overload metrics, an overload threshold was needed. The overload threshold for this model was determined by asking 2 SMEs to provide 95% confidence intervals for the percentage of a week they are overloaded. Overload is defined as the times when a worker is behind on tasks, task performance is suffering, and the worker is losing track of the big picture. Candidate overload thresholds were applied to the IMPRINT workload outputs and compared with the SME estimates. The VACP value of 35 was selected as the overload threshold. Details on establishing the overload threshold are provided in Appendix G – Overload Threshold Determination.

Alternate Model Creation

Once the validated baseline model was completed, alternate models which represent the MSU under different patient loads were created. Based on the MSU expectation of a 30% increase to inpatient units, the researchers created 5 alternate models which simulate the MSU under patient load increases of 10%, 20%, 30%, 40%, and 50% in order to fully explore potential future patient loads. The alternate models were made by altering the baseline model to account for increased patient arrivals. In the baseline model, patients are generated using distributions which determine the time between new patients. The patient load is increased by dividing these distributions by a Patient Load Multiplier value. The researchers created the 5 alternate models using the Patient Load Multiplier values shown in Table 12.

Table 12: Alternate Model Patient Loads

Model	Patient Load Multiplier Value
10% Increase	1.1
20% Increase	1.2
30% Increase	1.3
40% Increase	1.4
50% Increase	1.5

Analysis and Results

The researchers used three throughput metrics (Weekly Discharge, Bed Utilization, and Turned Away Patients) to verify that the alternate models increased the patient load as intended. Table 13 shows the weekly discharge and bed utilization values which increase as expected for each alternate model. The number of turned away patients is important because it reduces the effects of patient load on medical staff mental workload (i.e. if there were more beds, then medical staff workload would be higher). As Table 13 shows, the model predicts that zero patients will be turned away in the baseline model which matches the real-world MSU records. The number of turned away patients incrementally increases up to 2.23 patients per week at the 50% increase level. This number of turned away patients has a negligible effect on the workload metrics because there are an average of 77.79 discharges each week at the 50% increase. However, turning away any number of patients could be viewed negatively and is something which the medical center leadership may be interested in.

Table 13: Alternate Model Throughput Metrics

		Baseline	10%	20%	30%	40%	50%
WeeklyDischarge	**Average**	52.92	58.45	63.71	67.61	73.69	77.79
(3rd weeks of 104 runs)	**Std Dev**	6.68	6.28	7.35	7.54	7.30	6.81
BedUtilization	**Average**	20.40	21.00	24.32	24.54	29.18	30.46
(28 days, 3rd week of 4 runs)	**Std Dev**	5.17	5.03	3.99	5.39	6.04	5.16
TurnedAwayPTs	**Total**	0.00	7.00	26.00	44.00	187.00	232.00
(3rd weeks of 104 runs)	**Avg # / week**	0.00	0.07	0.25	0.42	1.80	2.23

The IMPRINT model was used to evaluate 5 different workload metrics: idle time, average workload, overload percent, cumulative time spent on each task, and cumulative time spent on each task while overloaded. Idle time is the time a worker is at zero VACP workload. Average workload is the time-weighted average of the VACP value for each worker over the course of the one-week period. Overload percent is the percentage of time that each worker is over the overload threshold. The cumulative time spent on each task is generated by summing the amount of time spent over the week performing a particular task. The time spent on each task while overloaded is generated by summing the amount of time spent over the week that a worker is overloaded while performing a specific task.

While the IMPRINT model includes 6 nurses, 4 technicians, a shift leader, and a charge nurse, only the results of 1 nurse, 1 technician, the shift leader, and the charge nurse are shown. The nurse and technician with the highest patient load (nurse1 and technician1) are shown since they are the most extreme of their staff type. For all workload metrics except for overload percent, nurse1 is statistically different than all other nurses. Technician1 is statistically different than the other technicians for all workload metrics. Nurse1 and technician1 have the highest patient load because they

receive the remainder after all patients have been evenly distributed. For specific information on the patient assignment logic, view Appendix H – Patient Load Alternate Models.

The ANOVA 95% confidence intervals and Tukey groupings for the idle time, average workload, and overload time are shown in Tables 14-16. The average for each of the three metrics are graphed in Figures 4-6. Additionally, Tables 17-20 show the cumulative time spent on each task and the cumulative time spent on each task while overloaded. The idle time, average workload, and overload time are determined using 60 IMPRINT replications. The explanation for the number of replications used is provided in Appendix D – Baseline Model. The number of runs used to find the cumulative and overload task time metrics in Tables 17-20 were limited to 10 IMPRINT replications due to intensive post-processing requirements.

Idle Time

For idle time, nurse1, technician1, and the shift leader all have the same tukey groupings: all patient load levels are statistically different except between 20% and 30% and between 40% and 50%. For the charge nurse, every patient load level is statistically different. Figure 4 fits a line to the average idle time for each staff member at each patient load level. For each of the four staff types, the relationship between patient load and idle time is linear (R^2 values greater than 0.975). Nurse1 has the most negative slope (-0.4205) and the charge nurse has the least negative slope (-0.0989).

Table 14: Idle Time ANOVA (n=60)

Staff	Nurse1		Technician1		Charge Nurse		Shift Leader	
One-way ANOVA	[F(5, 354) = 76.87, p = 0.000]		[F(5, 354) = 73.85, p = 0.000]		[F(5, 354) = 109.96, p = 0.000]		[F(5, 354) = 75.16, p = 0.000]	
	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings
Baseline	(0.34980, 0.38550)	A	(0.47005, 0.49640)	A	(0.47130, 0.47825)	A	(0.53601, 0.56499)	A
10%	(0.28493, 0.32061)	B	(0.42027, 0.44662)	B	(0.46051, 0.46746)	B	(0.48502, 0.51400)	B
20%	(0.24558, 0.28126)	C	(0.38833, 0.41468)	C	(0.45036, 0.45731)	C	(0.45024, 0.47922)	C
30%	(0.20979, 0.24547)	C	(0.36837, 0.39472)	C	(0.44284, 0.44979)	D	(0.42634, 0.45532)	C
40%	(0.15536, 0.19104)	D	(0.33000, 0.35635)	D	(0.42999, 0.43694)	E	(0.38059, 0.40957)	D
50%	(0.14032, 0.17600)	D	(0.31552, 0.34187)	D	(0.42187, 0.42883)	F	(0.36691, 0.39589)	D

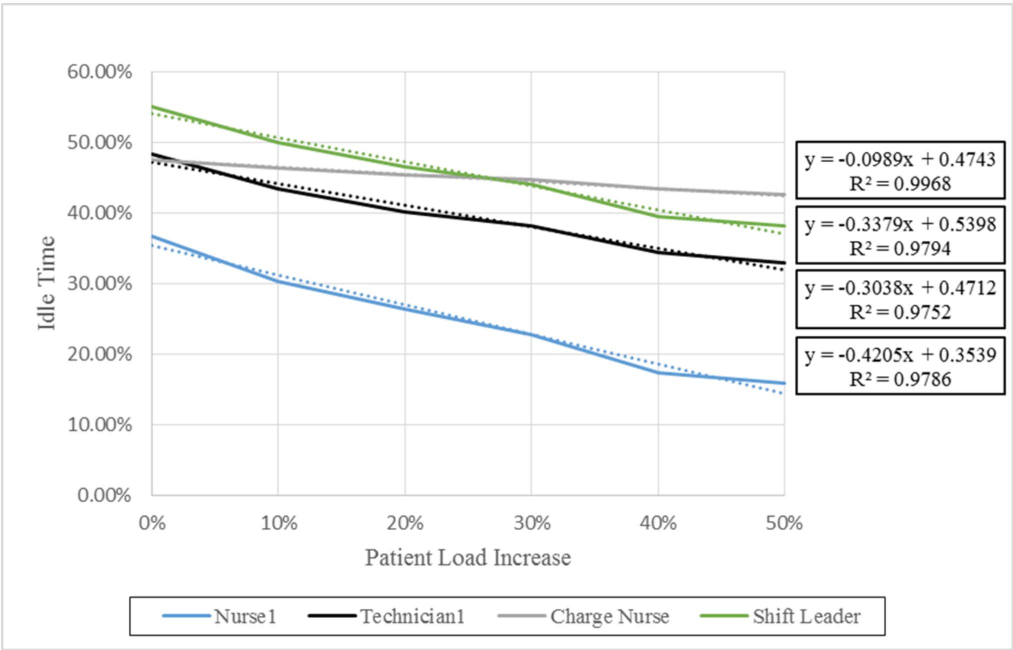

Figure 4: Average of Idle Time (n=60)

Average Workload

For average workload, the technician1, the charge nurse, and the shift leader all have the same tukey groupings: all patient load levels are statistically different except between 20% and 30% and between 40% and 50%. For nurse1 all patient load levels are statistically different except between 40% and 50%. Figure 5 fits a line to the average

workload for each staff member at each patient load level. For each of the four staff types, the relationship between patient load and average workload is linear (R^2 values greater than 0.973). Nurse1 has the greatest slope (8.9432) and the charge nurse has the smallest slope (2.8523).

Table 15: Average Workload ANOVA (n=60)

Staff	Nurse1		Technician1		Charge Nurse		Shift Leader	
One-way ANOVA	[F(5, 354) = 83.02, p = 0.000]		[F(5, 354) = 73.80, p = 0.000]		[F(5, 354) = 110.33, p = 0.000]		[F(5, 354) = 76.44, p = 0.000]	
	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings
Baseline	(12.900, 13.629)	A	(10.336, 11.074)	A	(8.927, 9.127)	A	(8.109, 8.853)	A
10%	(14.248, 14.977)	B	(11.593, 12.332)	B	(9.279, 9.479)	B	(9.319, 10.062)	B
20%	(15.122, 15.851)	C	(12.545, 13.283)	C	(9.563, 9.763)	C	(10.236, 10.979)	C
30%	(15.928, 16.657)	D	(13.009, 13.747)	C	(9.744, 9.945)	C	(10.836, 11.579)	C
40%	(16.974, 17.703)	E	(14.312, 15.050)	D	(10.157, 10.358)	D	(12.067, 12.810)	D
50%	(17.364, 18.093)	E	(14.562, 15.300)	D	(10.360, 10.560)	D	(12.474, 13.217)	D

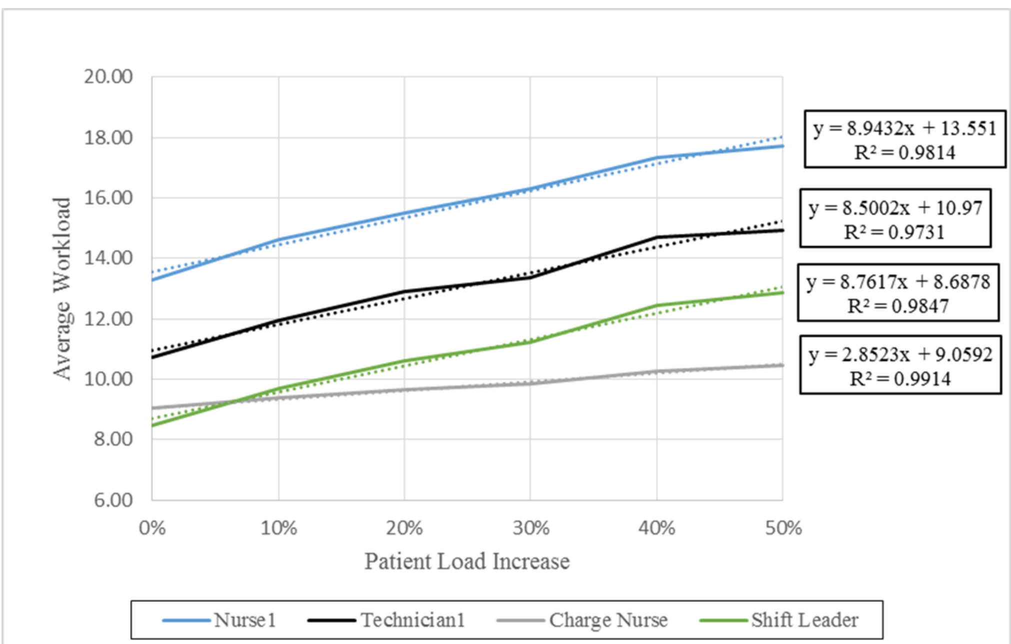

Figure 5: Average of Average Workload (n=60)

Overload Time

For overload time, technician1 and the shift leader have the same tukey groupings: all patient load levels are statistically different except between 20% and 30% and between 40% and 50%. For the charge nurse, all patient load levels are statistically different except between 10%, 20%, and 30% and between 40% and 50%. For nurse1, the changes to average workload are so minor that no adjacent 10% changes in patient load are statistically different from each other; it takes at least a 20% change in patient load for differences to become significant. Figure 6 fits a line to the overload time for each staff member at the patient load levels. For each of the four staff types, the relationship between patient load and idle time is linear (R^2 values greater than 0.894). Technician1 has the greatest slope (0.1081) and the charge nurse has the smallest slope (0.017).

Table 16: Overload Time ANOVA (n=60)

Staff	Nurse1		Technician1		Charge Nurse		Shift Leader	
One-way ANOVA	[F(5, 354) = 13.39, p = 0.000]		[F(5, 354) = 63.73, p = 0.000]		[F(5, 354) = 41.28, p = 0.000]		[F(5, 354) = 61.74, p = 0.000]	
	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings	95% CI	Tukey Groupings
Baseline	(0.04889, 0.05388)	A	(0.05571, 0.06586)	A	(0.019719, 0.021707)	A	(0.02863, 0.03693)	A
10%	(0.05300, 0.05800)	AB	(0.06890, 0.07905)	B	(0.022358, 0.024346)	B	(0.03824, 0.04654)	B
20%	(0.05611, 0.06110)	BC	(0.08304, 0.09318)	C	(0.023729, 0.025717)	B	(0.04831, 0.05661)	C
30%	(0.05962, 0.06462)	CD	(0.08738, 0.09753)	C	(0.024189, 0.026177)	B	(0.05420, 0.06250)	C
40%	(0.05807, 0.06307)	BCD	(0.10674, 0.11689)	D	(0.027568, 0.029556)	C	(0.06718, 0.07549)	D
50%	(0.06159, 0.06659)	D	(0.10781, 0.11796)	D	(0.028420, 0.030409)	C	(0.07184, 0.08014)	D

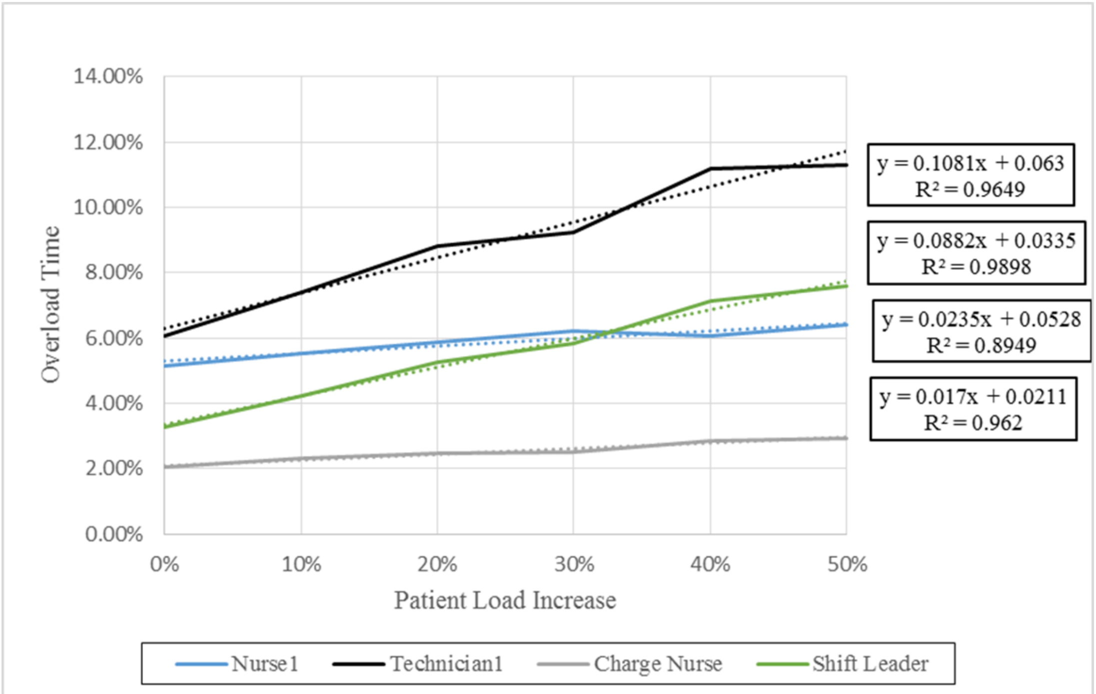

Figure 6: Average of Overload Time (n=60)

Task Time Metrics

For each of the staff types, the sum of the overload time and total time increases as patient load increases. The sum of the percent overload column remains nearly unchanged for nurse1, increase from 22% to 28% for technician1, increases from 9% to 12% for the charge nurse, and increases from 14% to 22% for the shift leader. Evaluating the values for each individual task provides specific information on how each task changes as patient load increases.

Table 17: Nurse1 Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
Administer Meds	5.21	15.05	37%	5.15	18.84	28%	4.86	20.24	25%
Close/Turn In Records	0.09	1.36	6%	0.24	1.80	13%	0.35	2.02	17%
Complete Admission Notes	0.13	2.39	5%	0.23	3.56	7%	0.22	3.71	6%
Full Assessment	4.56	13.82	35%	4.23	16.23	27%	4.09	18.24	23%
Handle Call Light	1.94	7.71	24%	2.93	9.37	31%	3.58	9.65	37%
Nurse 1 Shift Change	0.15	7.61	2%	0.35	7.61	4%	0.33	6.91	5%
Collect Labs	0.07	2.54	3%	0.13	3.68	4%	0.24	3.56	7%
Nurse D/C Patient	0.05	0.95	5%	0.02	1.24	2%	0.07	1.10	8%
Perform Admission Orders	1.35	6.90	18%	2.54	9.41	26%	2.92	10.13	28%
Perform Discharge Orders	0.62	1.59	39%	1.15	2.21	54%	1.48	2.39	61%
Prepare Discharge Papers	0.31	1.15	29%	0.51	1.73	29%	0.36	1.70	21%
Prepare PT for D/C	0.37	1.70	22%	0.49	2.28	22%	0.59	2.33	25%
Preview Orders/Patient Info	0.01	0.75	2%	0.07	1.06	7%	0.06	1.22	4%
Q2h Rounding	3.28	53.07	6%	4.06	62.03	7%	4.11	67.63	6%
Receive Report	0.20	1.78	11%	0.66	2.64	24%	0.72	2.70	27%
Room Prep	0.03	0.90	2%	0.07	1.31	5%	0.01	1.36	1%
Strip Room	0.03	1.32	2%	0.10	1.83	6%	0.12	1.89	6%
Total	18.38	120.58	15%	22.93	146.83	16%	24.10	156.76	15%

Table 18: Technician1 Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
Handle Call Light	6.33	20.03	30%	10.00	25.99	38%	11.90	29.26	41%
Q2h Rounding	3.85	30.81	12%	6.06	39.47	15%	6.53	42.25	15%
Remove Invasive Devices	0.09	1.20	6%	0.19	1.51	13%	0.19	1.88	10%
Retreive from Test	0.30	3.86	7%	0.61	4.49	13%	0.64	5.24	12%
Room Prep	0.10	1.17	8%	0.21	1.35	15%	0.27	1.69	15%
Strip Room	0.13	1.70	8%	0.23	2.00	10%	0.37	2.50	15%
Tech 1 Shift Change	0.02	2.22	1%	0.03	2.13	1%	0.06	2.21	3%
Collect Lab	0.48	6.05	8%	0.43	6.43	7%	0.62	7.29	9%
Tech D/C Patient	0.14	1.71	7%	0.24	2.03	12%	0.31	2.68	14%
Transport to Test	0.40	3.72	9%	0.56	4.64	12%	0.79	5.40	15%
Vitals, I/O, Neuro	11.33	31.25	35%	16.32	39.49	41%	19.20	43.67	44%
Total	23.18	103.71	22%	34.87	129.53	27%	40.87	144.07	28%

Table 19: Charge Nurse Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
72 Hour Callbacks	0.24	5.78	4%	0.25	7.31	4%	0.32	8.03	4%
Assign Patient to Room/Nurse	3.32	9.96	33%	4.27	12.55	33%	5.37	14.80	36%
Bed Meeting (0745, M-F)	0.53	1.39	38%	0.54	1.47	37%	0.61	1.50	40%
Charge Rounds	1.32	16.56	8%	1.53	15.68	10%	1.88	17.20	11%
Clean Nurse Station (0715/1915)	0.05	2.27	2%	0.05	2.31	2%	0.06	2.39	3%
CN Shift Change	0.27	8.19	3%	0.51	8.18	6%	0.67	8.13	8%
Handle Call Light	0.59	5.61	10%	0.98	7.37	13%	1.26	7.36	16%
Help Visitors/Phone Calls	2.77	48.09	6%	3.25	48.19	7%	3.94	47.78	8%
Internal Med Meeting (830)	0.77	3.32	23%	0.87	3.24	27%	0.95	3.32	29%
Nurse, Q Sunday Night Tasks	0.01	0.80	2%	0.01	0.72	1%	0.00	0.75	0%
Restock Med Room	0.11	3.08	4%	0.16	3.15	5%	0.14	3.10	5%
Update board/journal/WMSN	0.15	10.07	2%	0.25	13.26	2%	0.40	15.01	3%
Total	10.13	115.11	9%	12.68	123.43	10%	15.60	129.36	12%

Table 20: Shift Leader Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
Assign Patient to Tech	0.88	4.36	20%	1.57	5.84	26%	1.96	6.72	29%
Handle Call Light	3.80	14.78	25%	6.08	17.60	33%	7.75	21.37	36%
Misc Cleaning	0.07	6.12	1%	0.13	6.09	2%	0.27	5.71	5%
Q2h Rounding	1.81	20.90	8%	3.32	27.27	12%	4.00	31.94	13%
Remove Invasive Devices	0.04	0.80	5%	0.10	1.08	10%	0.15	1.34	11%
Restock PT & Supply Rooms	0.11	6.00	2%	0.21	5.91	3%	0.30	5.93	5%
Retreive from Test	0.12	2.66	4%	0.31	3.77	8%	0.50	3.66	14%
Room Prep	0.05	0.70	6%	0.15	0.99	14%	0.17	1.18	14%
Shift Ldr Misc Checks	0.31	4.06	8%	0.85	4.03	21%	0.53	4.07	13%
Shift Ldr Shift Change	0.24	4.46	5%	0.67	4.53	15%	0.37	4.35	9%
Strip Room	0.04	1.08	4%	0.11	1.36	8%	0.19	1.71	12%
Collect Lab	0.15	3.54	4%	0.28	4.77	5%	0.33	4.69	7%
Tech D/C Patient	0.04	1.14	4%	0.05	1.04	4%	0.25	1.71	15%
Tech, Q Sunday Night Tasks	0.00	0.46	0%	0.00	0.47	0%	0.01	0.47	2%
Transport to Test	0.20	2.65	7%	0.52	3.86	12%	0.53	3.85	14%
Vitals, I/O, Neuro	5.70	20.85	27%	7.99	27.57	29%	11.39	31.69	36%
Total	13.56	94.54	14%	22.33	116.19	19%	28.69	130.40	22%

Investigative Question 1

1. "What is the relationship between patient load and medical staff mental workload metrics (idle time, average mental workload, overload time)?"

Figures 4-6 indicate that, for all staff members, idle time decreases, average workload increases, and overload time increases as patient load increases. The

relationship for each of these metrics is linear with R^2 values ranging from 0.8949 to 0.9968. For idle time, the slopes range from -0.4205 to -0.0989 percent time per percent patient load increase. For average workload, the slopes range from 2.852 to 8.9432 VACP value per percent patient load increase. For overload time, the slopes range from 0.017 to 0.108 percent time per percent patient load increase.

Investigative Question 2

2. "Which medical staff workers experience the greatest negative impact in mental workload metrics as patient load increases?"

Figures 4-6 show that nurse1 and technician1 were the most impacted by increases in patient load. Nurse1 has the greatest slope for idle (-0.4205) and average workload (8.9432) compared to the other staff members. However, the difference between nurse1, technician1, and the shift leader are relatively small. Similarly, technician1 has the greatest slope for overload time (0.1081) compared to the other staff types. However, the difference between technician1 and the shift leader was small. A concerning characteristic about these three metrics are that the staff type with the greatest slope was also the same staff member who has the most extreme value to start with. For example, nurse1 starts off with the lowest amount of idle time at the baseline level and has the largest slope. Ultimately, this results in an increase in the spread in workload metric values for the different staff members as patient load increases.

Investigative Question 3

3. "How does patient load influence individual task performance (total task times and overload task times)?"

The researchers found the total time and the total time overloaded in a week that each task was performed for each staff type. Overload time is used to infer the quality of task performance. The complete set of data is shown in Tables 17-20. By comparing the totals of the two task time metrics of the baseline model and 50% increase, it is found that nurse1 total time spent on tasks increases by 30% and overload time increases by 31%, technician1 total time spent on tasks increases by 39% and overload time increases by 76%, the charge nurse total time spent on tasks by increases by 12% and overload time increases by 54%, the shift leader total time spent on tasks increases by 38% and overload time increases by 211%.

Discussion

The general relationship between the medical staff idle time, average workload, and overload time is intuitive. The linear behavior of these metrics allows us to conclude that workload metrics are proportionally related to patient load between the baseline and a 50% patient load increase. Further increasing the patient load beyond the 50% increase could provide interesting information about the limits of each metric.

The results of investigative question two are due to task differences between staff member. Nearly all of nurse and technician tasks are related to specific patients, so an increased patient load will impact them significantly more than the charge nurse and shift leader who have more "overhead" tasks which are not influences by patient load. There

are also differences between nurses and technicians which help explain the results. Nurses have more long, infrequent, and non-urgent tasks which allows for a more level workload than technicians who have more short, frequent, and urgent tasks. This explains why nurses have the least idle time, highest average workload, and a moderate overload time and why technicians have the highest overload time, moderate average workload, and moderate idle time.

The influence of patient load on total task time depends on task type. There are two main types of tasks performed by the medical staff: tasks caring for a specific patient and "overhead" tasks which are performed regardless of patient load. For the most part, the IMPRINT model predicts that tasks which were directly related to caring for patients increased almost proportionally to the patient load increases while overhead tasks remain nearly unchanged. Even though each individual task changed in a trivial way, the combination of these tasks for each staff types provides insightful results.

While the overload time of most tasks increase as patient loads increase, there is a difference between urgent and non-urgent tasks. On average, the increases in overload time of urgent tasks is greater than non-urgent tasks. These results infer that the quality of task performance will decrease for all task types; however, urgent tasks will experiences the greatest decrease in performance. Since technicians and shift leaders have many urgent tasks, they are expected to experience the greatest decrease in task performance.

Conclusion

In general, the relationship between patient load and workload metrics are as expected: as patient load increases, idle time decreases, average workload increases, and overload time increases. Nurses and technicians are the most influenced by patient loads because they have the highest ratio of patient specific tasks to "overhead" tasks. The changes to individual tasks overload and total time reveal how the employees with many short, frequent, and urgent tasks are much more prone to being overload at increased patient loads compared to staff who have many long, infrequent, and less urgent tasks. Given the results of this study and the fact that the MSU is high performing (low error rates) under current conditions, the researchers believe that the MSU is capable of safely handling a 30% increase in patient load. The researchers recommend that patient load is increased incrementally and that the performance of the medical staff is monitored. Specifically, technicians should be closely monitored due to their high overload time which could lead to medical errors.

Since the model does not include any dynamic task balancing logic, the spread between staff types for each workload metric becomes more extreme as patient load increases. The incorporation of workload balancing policies into the MSU could reduce the spread by leveling out each metric. For future research, an alternate model will be created to simulate the MSU with a workload balancing task.

V. Exploring the Effects of Task Sharing on Medical Staff Mental Workload using Simulation

Abstract

Many process improvement initiatives have been performed in response to increasing demands on the United States healthcare system. Some of these initiatives have included Lean manufacturing principles. An important Lean principle is called heijunka which is the leveling of workload. Balanced workload levels are important for human performance and efficiency. This study uses simulations to evaluate how task sharing influences the balance of medical staff mental workload. The results, which are only applicable for the modeled unit, indicate that task sharing improves the balance of idle time and average workload; however, it makes overload time more unbalanced. Additional workload policy changes are recommended to overcome the negative results of the overload time metric.

Introduction

Concerns over increasing demands on the United States healthcare system have sparked many process improvement initiatives. Process improvements can be very beneficial because it has been postulated that over 90% of performance issues are due to poor system design (Deming, 2000; Scholtes et al., 2003). Some hospitals have worked to improve their systems by applying Lean manufacturing principles (Hintzen, Knoer, Van Dyke, & Milavitz, 2009; Lamm, Eckel, Daniels, & Amerine, 2015; Naik et al., 2012). Lean principles use philosophies based on the Toyota Production System which focuses on eliminating waste (Liker, 2004).

One of the first steps in creating a Lean system is to level workload, commonly known as heijunka (Liker, 2004). Uneven workload is inefficient because it makes some resources under-or over-utilized at times. An uneven medical staff workload reduces human performance due to the Hebb-Yerkes-Dodson Law which states that human performance is worst at low and high workloads (Teigen, 1994; Yerkes & Dodson, 1908). Additionally, high workloads have been found to negatively impact patient satisfaction (Feddock et al., 2005). In the medical field, heijunka usually refers to the leveling of patient flow which has been the focus of many research articles (Graban, 2011; Yahia, Harraz, & Eltawil, 2014). While leveling patient flow over time is important, it is also important to level patient load between staff members.

The Improved Performance Research Integration Tool (IMPRINT) is a discrete-event simulation tool which can be used to evaluate the mental workload of medical staff. Recent research using IMPRINT to evaluate an inpatient unit at the Wright-Patterson Medical Center found large differences in idle time, overload time, and average workload between staff members, as provided in Chapter IV. Additionally, these differences became more extreme as patient loads increase. The unevenness is due to an inconsistent and unstandardized task sharing policy in the unit.

Objective

Leaders in the 88th Medical Group are looking for ways to improve their system because they are expecting a 30% increase in patient load from local Veteran's Affairs clinics (Mort, 2015). After using IMPRINT to evaluate an inpatient unit, the researchers hypothesize that workload metrics (idle time, average workload, and overload time) can be improved by balancing the workload of medical staff members by allowing for task

sharing. Therefore, the objective of this researcher is to evaluate the influence of task sharing on medical staff mental workload metrics (idle time, average workload, overload time) using IMPRINT. The results will have potential benefits to the Wright-Patterson Medical Center and demonstrate the usefulness of simulation for predicting process improvement outcomes.

Methodology

This research uses IMPRINT to model the Medical Surgical Unit (MSU) on Wright-Patterson Air Force Base. The MSU primarily cares for patients recovering from surgeries or emergencies. It has 39 beds and an average staff of 6 nurses, 4 technicians, 1 charge nurse, and 1 shift leader. Specific details on the MSU and how the IMPRINT model was built are described in Section 2 of Chapter III.

In the MSU, "Q2h rounding" is a common task performed by nurses, technicians, and the shift leader. It is used to check on patients and help them if they have any issues. The task is scheduled to be performed every 2 hours; however, the task can be postponed because it only starts when the assigned staff member is not performing any other tasks. In the current system, as with all other tasks, "Q2h rounding" is not shared between staff members in the MSU. However, it is hypothesized that it may be a good task to share because it is performed very often and is simple; it does not require any special qualifications and carries little liability.

Since the MSU leadership is expecting a 30% patient load increase, a model which represents this patient load increase is used as a baseline model for this research. An alternate model is then created by modifying the baseline model by allowing the "Q2h

rounding" task to be shared. The task network differences between the baseline and alternate model can be seen in Figure 7 and Figure 8. The "Staff Select" node is used in the alternate model to assign the "Q2h rounding" task to a staff member who is free at the moment (or the first to become free). The "Staff Select" task starts by checking the assigned staff member to see if they are performing any tasks at the moment. If they are not performing any tasks, the assigned staff member is assigned the task and starts immediately. If they are busy, the next staff member in the list is checked. This process continues down the list (and loops back up to the top when at the bottom) until a staff member is selected. The task can be shared between any staff type, including the Charge Nurse who normally does not perform "Q2h rounding." The model assumes perfect work ethic which means there are no attempts to avoid task sharing.

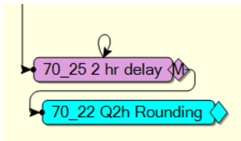

Figure 7: Baseline Model "Q2h Rounding" Task Network

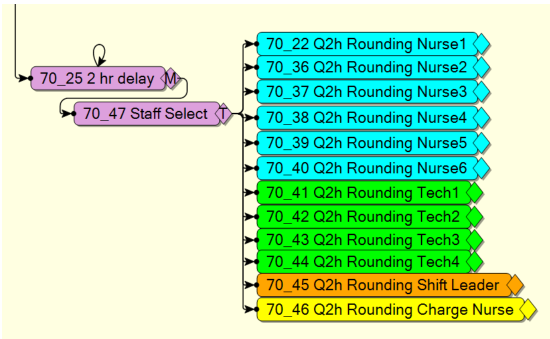

Figure 8: Alternate Model "Q2h Rounding" Task Network

In the real-world, the alternate model could be implemented using a timer with a light near the door of each patient's room. Every time that a staff member checks on a patient, the timer is reset. If it has been over 2 hours, then the light will turn on, thus notifying nearby staff members that the patient needs to be checked. Any staff member who is not performing a task at that moment and notices the light would immediately check on the patient.

For this research, the independent variable is the task sharing of the "Q2h rounding" task. The dependent variables are idle time; average workload; overload time; cumulative time spent on each task; and cumulative time spent on each task while overloaded. An explanation of how each variable is calculated was previously described in Chapter III, *Variables and Model Replications*.

To statistically evaluate the workload metrics, both IMRPINT models were run 30 times. The number of runs was calculated using the half-width of the weekly discharge metric which indicates how many patients were discharged during the model run. Weekly discharge is used because it has a major influence on workload metrics. It was determined that a half-width under 2.5 is acceptable given that real-world weekly discharge half-width is 2.18. After 30 runs, the baseline model weekly discharge half-width equaled 2.28. The task time metrics, in Tables 24-27, only use 10 of the 30 IMPRINT runs because they required time consuming post-processing.

To verify that changes between the baseline and alternate models are due to the changes to "Q2h rounding," and not due to differences in patient load, the weekly discharge metric of the baseline model and alternate model are statistically compared. The P-value for the baseline and alternate model weekly discharge metric is 0.298;

therefore, there is not a statistical difference in patient load between the two models when evaluated against a statistical significance level of 0.1.

Results

As Table 21 and Figure 9 show, the idle time increases for the first 4 nurses and decreases for all other staff members which results in a more level idle time between all staff members. The range between the staff members with the most and least amount of idle decreases from 22.14% to 7.48%. All of the staff members except nurse3-6 had statistically significant changes to idle time. An interesting result is that the average idle time of all staff members' decreases by 6.03% despite the weekly discharge increasing by only 2.9% (due to randomness). However, neither changes are statistically significant (weekly discharge p-value=0.298, average idle time p-value=0.115).

Table 21: Idle Time Results (n=30)

	Baseline Model		Alternate Model			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**P-value**
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	22.43%	4.40%	33.12%	6.78%	10.68%	0.000
Nurse2	24.39%	5.27%	30.70%	5.96%	6.32%	0.000
Nurse3	28.07%	6.18%	29.97%	5.68%	1.89%	0.222
Nurse4	29.02%	6.68%	29.89%	5.88%	0.87%	0.594
Nurse5	32.32%	6.07%	30.54%	6.15%	-1.78%	0.264
Nurse6	33.73%	6.79%	31.11%	6.44%	-2.63%	0.130
Technician1	37.88%	4.28%	32.62%	5.97%	-5.26%	0.000
Technician2	39.59%	4.57%	33.92%	6.67%	-5.67%	0.000
Technician3	41.67%	4.12%	34.84%	6.60%	-6.84%	0.000
Technician4	42.90%	4.54%	36.91%	6.59%	-5.98%	0.000
Charge Nurse	44.57%	1.34%	34.35%	3.96%	-10.22%	0.000
Shift Leader	44.14%	4.47%	37.37%	6.80%	-6.77%	0.000
Average	35.06%	-	32.94%	-	-2.11%	0.115

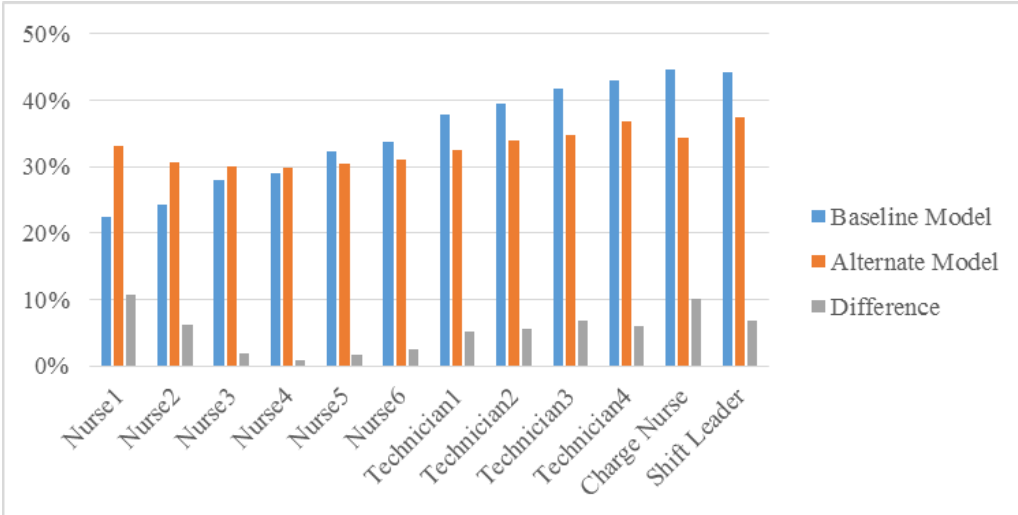

Figure 9: Idle Time

The results of the average workload metric are shown in Table 22 and Figure 10. Similar to idle time, the average workload decreases for the first 4 nurses and increases for all other staff members which results in a more level average workload between all staff members. The range between the staff members with the highest and smallest average workload decreases from 6.52 to 2.68. Again, all of the staff members except nurse3-6 had statistically significant changes to average workload. Similar to idle time, the average of the average workloads of all staff members' increase by 5.93% despite the weekly discharge not being statistically significant. Unlike idle time, the average workload difference was statistically significant (p-value=0.021).

Table 22: Average Workload Results (n=30)

	Baseline Model		Alternate Model			
	Mean	SD	Mean	SD	Difference	P-value
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	16.37	0.97	14.64	1.67	-1.73	0.000
Nurse2	15.86	1.11	14.84	1.48	-1.02	0.004
Nurse3	15.07	1.34	14.98	1.53	-0.09	0.802
Nurse4	14.93	1.36	14.81	1.39	-0.13	0.717
Nurse5	14.34	1.23	14.75	1.53	0.41	0.258
Nurse6	13.96	1.35	14.35	1.56	0.39	0.301
Technician1	13.46	1.22	15.12	1.74	1.67	0.000
Technician2	13.07	1.23	14.77	1.92	1.70	0.000
Technician3	12.43	1.19	14.39	1.93	1.96	0.000
Technician4	12.04	1.25	13.96	1.81	1.92	0.000
Charge Nurse	9.85	0.43	12.45	1.07	2.59	0.000
Shift Leader	11.14	1.15	13.11	1.87	1.97	0.000
Average	13.54	-	14.35	-	0.80	0.021

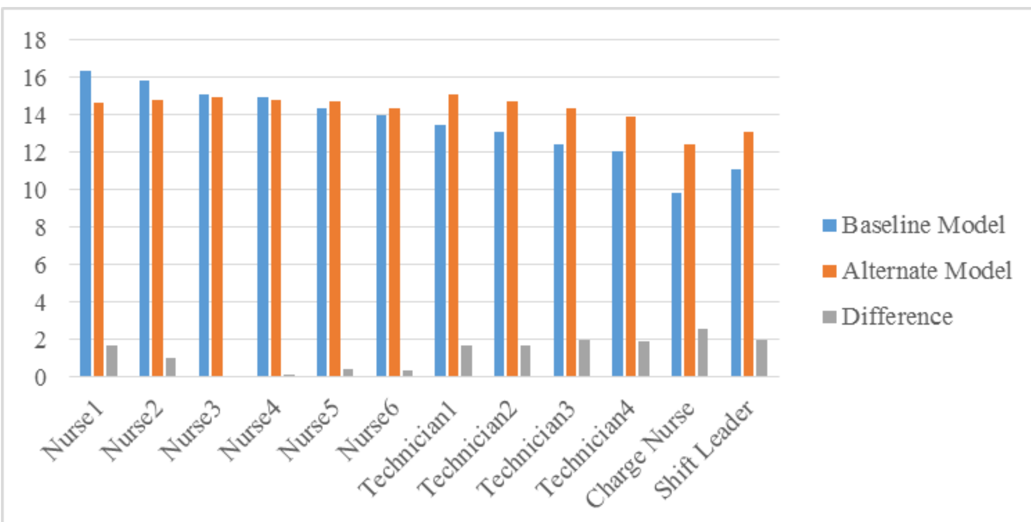

Figure 10: Average Workload

As Table 23 and Figure 11 show, the results for overload time are different than the previous two metrics. The overload time decreases for each nurse and increases for all other staff members, making the overload time less balanced. Unfortunately, the range between the staff members with the most and least amount of overload time increased from 6.73% to 8.29%. All changes were statistically significant except for the changes to nurse1-3. Similar to the other metrics, the average overload time increases by 9.5% despite weekly discharge not being statistically significant. Like average workload, the differences for overload time is statistically significant (p-value=0.019).

Table 23: Overload Time Results (n=30)

	Baseline Model		Alternate Model			
	Mean	**SD**	**Mean**	**SD**	**Difference**	**P-value**
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	6.21%	1.16%	6.16%	1.15%	-0.05%	0.860
Nurse2	6.01%	1.07%	5.54%	1.14%	-0.47%	0.108
Nurse3	5.73%	0.83%	5.60%	1.00%	-0.13%	0.571
Nurse4	5.77%	0.97%	5.05%	0.94%	-0.71%	0.005
Nurse5	6.02%	0.95%	5.36%	0.88%	-0.66%	0.007
Nurse6	5.46%	0.67%	4.64%	0.96%	-0.83%	0.000
Technician1	9.25%	1.78%	11.23%	2.60%	1.97%	0.001
Technician2	9.05%	1.53%	10.80%	2.65%	1.75%	0.003
Technician3	7.99%	1.60%	9.95%	2.50%	1.95%	0.001
Technician4	7.46%	1.65%	9.70%	2.25%	2.24%	0.000
Charge Nurse	2.52%	0.45%	2.94%	0.42%	0.42%	0.000
Shift Leader	5.59%	1.25%	7.46%	2.24%	1.87%	0.000
Average	6.42%	-	7.04%	-	0.61%	0.019

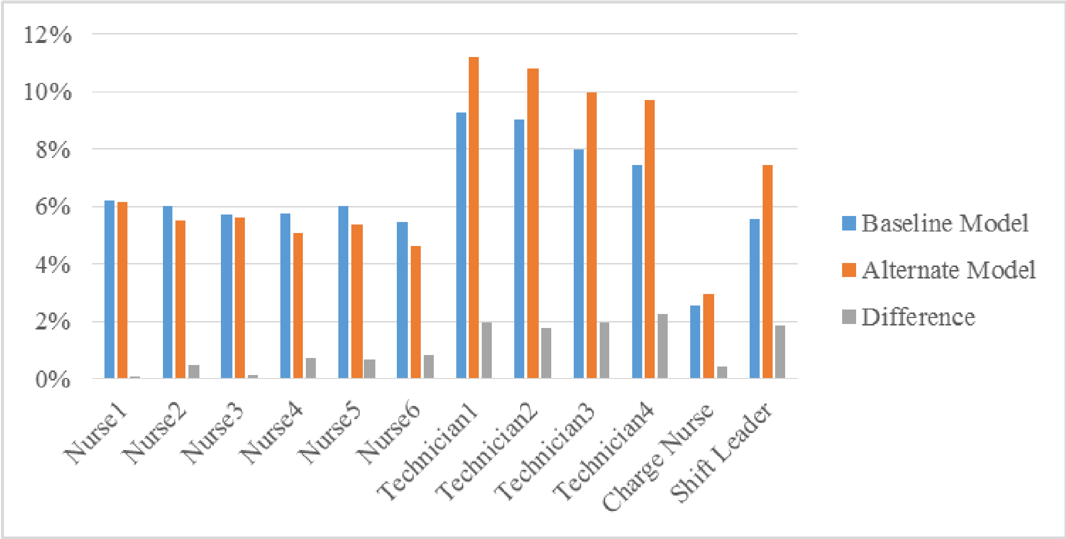

Figure 11: Overload Time

Tables 24-27 show how the total and overload time spent on each task changes. The changes help to explain why idle time and average workload become more level and why overload time becomes less level. As expected, the biggest changes occur to “Q2h rounding” for each staff member. “Q2h rounding” decreases by 20.57 hours for nurse1, increases by 13.76 hours for technician1, increases by 24.13 hours for the change nurse, and increases by 13.13 hours for the shift leader. These changes result in an overall increase in overload percent for the technician1 and shift leader and almost no change in the overload percent for the nurse1 and the charge nurse.

Table 24: Nurse1 Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Administer Meds	5.15	18.84	28%	5.53	20.88	27%
Close/Turn In Records	0.24	1.80	13%	0.15	1.73	9%
Complete Admission Notes	0.23	3.56	7%	0.18	2.98	6%
Full Assessment	4.23	16.23	27%	5.44	17.53	32%
Handle Call Light	2.93	9.37	31%	2.60	9.66	26%
Nurse 1 Shift Change	0.35	7.61	4%	0.23	7.59	3%
Collect Labs	0.13	3.68	4%	0.17	3.36	4%
Nurse D/C Patient	0.02	1.24	2%	0.04	1.22	3%
Perform Admission Orders	2.54	9.41	26%	1.51	8.41	17%
Perform Discharge Orders	1.15	2.21	54%	1.00	2.06	50%
Prepare Discharge Papers	0.51	1.73	29%	0.45	1.63	28%
Prepare PT for D/C	0.49	2.28	22%	0.58	2.12	28%
Preview Orders/Patient Info	0.07	1.06	7%	0.04	0.93	5%
Q2h Rounding	4.06	62.03	7%	1.19	41.46	3%
Receive Report	0.66	2.64	24%	0.41	2.22	19%
Room Prep	0.07	1.31	5%	0.02	1.06	1%
Strip Room	0.10	1.83	6%	0.08	1.60	5%
Total	**22.93**	**146.83**	**16%**	**19.61**	**126.43**	**16%**

Table 25: Technician1 Task Times (n=10)

Technician 1						
Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Handle Call Light	10.00	25.99	38%	11.46	27.01	42%
Q2h Rounding	6.06	39.47	15%	8.61	53.23	16%
Remove Invasive Devices	0.19	1.51	13%	0.18	1.59	11%
Retreive from Test	0.61	4.49	13%	0.76	5.06	15%
Room Prep	0.21	1.35	15%	0.18	1.44	12%
Strip Room	0.23	2.00	10%	0.29	2.11	14%
Tech 1 Shift Change	0.03	2.13	1%	0.03	2.20	1%
Collect Lab	0.43	6.43	7%	0.59	6.73	8%
Tech D/C Patient	0.24	2.03	12%	0.15	1.76	8%
Transport to Test	0.56	4.64	12%	0.77	5.18	15%
Vitals, I/O, Neuro	16.32	39.49	41%	19.25	41.01	47%
Total	**34.87**	**129.53**	**27%**	**42.27**	**147.30**	**29%**

Table 26: Charge Nurse Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
72 Hour Callbacks	0.25	7.31	4%	0.20	7.05	3%
Assign Patient to Room/Nurse	4.27	12.55	33%	4.96	12.76	39%
Bed Meeting (0745, M-F)	0.54	1.47	37%	0.53	1.46	36%
Charge Rounds	1.53	15.68	10%	1.76	16.27	11%
Clean Nurse Station (0715/1915)	0.05	2.31	2%	0.04	2.32	2%
CN Shift Change	0.51	8.18	6%	0.42	8.00	5%
Handle Call Light	0.98	7.37	13%	1.34	6.90	18%
Help Visitors/Phone Calls	3.25	48.19	7%	3.91	47.91	8%
Internal Med Meeting (830, M-F)	0.87	3.24	27%	0.97	3.33	29%
Nurse, Q Sunday Night Tasks	0.01	0.72	1%	0.00	0.84	1%
Q2h Rounding	0.00	0.00	0%	0.75	24.13	3%
Restock Med Room	0.16	3.15	5%	0.14	3.10	4%
Update board/journal/WMSN	0.25	13.26	2%	0.28	13.35	2%
Total	**12.68**	**123.43**	**10%**	**15.30**	**147.42**	**10%**

Table 27: Shift Leader Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Assign Patient to Tech	1.57	5.84	26%	1.60	5.85	27%
Handle Call Light	6.08	17.60	33%	7.48	19.72	38%
Misc Cleaning	0.13	6.09	2%	0.30	6.20	5%
Q2h Rounding	3.32	27.27	12%	5.29	40.40	13%
Remove Invasive Devices	0.10	1.08	10%	0.13	0.97	15%
Restock PT & Supply Rooms	0.21	5.91	3%	0.25	6.14	4%
Retreive from Test	0.31	3.77	8%	0.44	3.74	11%
Room Prep	0.15	0.99	14%	0.13	0.89	14%
Shift Ldr Misc Checks	0.85	4.03	21%	0.72	4.18	17%
Shift Ldr Shift Change	0.67	4.53	15%	0.59	4.51	13%
Strip Room	0.11	1.36	8%	0.10	1.34	7%
Collect Lab	0.28	4.77	5%	0.47	4.39	12%
Tech D/C Patient	0.05	1.04	4%	0.16	1.43	10%
Tech, Q Sunday Night Tasks	0.00	0.47	0%	0.01	0.53	3%
Transport to Test	0.52	3.86	12%	0.45	3.81	11%
Vitals, I/O, Neuro	7.99	27.57	29%	11.56	30.21	37%
Total	**22.33**	**116.19**	**19%**	**29.67**	**134.30**	**22%**

Discussion

The researchers hypothesized that allowing "Q2h rounding" to be shared among staff would help to level the mental workload metrics of the medical staff in the MSU. The premise is that the staff members who have fewer patients or less to do at a given moment will perform "Q2h rounding" for the workers who are busier. In general, this logic is likely true; however, it does not help to level overload time. A likely reason why the technicians and shift leader have the highest overload time, and had their overload time increase in the alternate model could be because they have mostly short, frequent, and urgent tasks. These workers end up spending more time idle or overloaded because their tasks are less predictable and need to be addressed quickly so they end up multitasking in short bursts. Since they originally had more idle time, they were more likely to start the "Q2h rounding" tasks compared to nurses. After starting "Q2h rounding," it is possible for an unrelated urgent task to come up which requires the technicians and shift leader to multitask, and possibly become overworked. The more tasks which technicians and shift leaders perform, the more likely for this sequence of events to occur.

A limitation with task sharing between staff members is that, ultimately, the same amount of work must be performed; the only difference is in who performs the work. Shifting workload is only beneficial up to a certain point. If many of the workers are idle or overloaded at the same time, improvements will need to be made by leveling the workload over time. Leveling the patient load over time, or changing staffing levels to match patient load, may be a promising topic for future research.

The decrease to the cumulative idle time and increase to cumulative average workload and overload time was unexpected. The researchers hypothesize that these results are due to fewer tasks being “dropped” in the alternate model. For example, in the baseline model, there are some non-urgent tasks being postponed because staff members are busy for stretches of time. It is possible for some number of tasks to be postponed until after a patient is discharged. Once a patient is discharged, all remaining tasks associated with that patient are “dropped.” Task sharing may help staff members to complete some of these tasks in a timely manner so that fewer of them are “dropped.” While this is a positive result, it would negatively impact the workload metrics. Detecting the rate of “dropped” tasks was not a primary objective of this research; however, preliminary research agrees with the hypothesis.

Measuring how timely staff members perform their tasks was also not a primary objective of this research. However, it is almost certainly the case that Q2h rounding is performed on time much more often in the alternate model. The secondary effects of prompt “Q2h rounding” would likely have positive effects on patient satisfaction, reduce fall rates, and reduce the number of call light. All of these potential effects, especially a reduction in call lights, could actually help to improve the workload metrics.

Conclusion

In the 88th Medical Group MSU, task sharing “Q2h rounding” helps to balance idle time and average workload; however, it makes overload time more unbalanced. Given the negative results of overload time, the researchers are hesitant to recommend the sharing of the “Q2h rounding” task. The increase in overload time for the

technicians, charge nurse, and shift leader outweigh the benefits of leveling idle time and average workload because an increase in overload time is likely to increase error rates. However, it may be possible to address the problems with overload time by implementing additional system changes. While the results of this study are unexpected, they still provide a number of insights. Discovering unintended consequences is one of the many benefits of simulation. It is better to discover that a system change does not perform as intended through simulation rather than the real-world where the stakes are usually higher.

Potential future work could involve testing other policy changes in addition to task sharing in an effort to level overload time. Leveling the patient load over time or changing staffing numbers to match patient load could have significant benefits on leveling workload metrics and may be worth evaluating.

VI. Conclusions and Recommendations

Chapter Overview

This chapter provides a general overview of current healthcare issues being faced in the United States. It then reiterates the overall research objectives of this paper. Following the objectives are three sections which explain the main findings of this research. The chapter concludes with recommendations for action for the 88th Medical Group Medical Surgical Unit (MSU) and recommendations for future research.

Research Motivation

Current estimates predict that 20% of Americans will be 65 or older by the year 2030 (Colby & Ortman, 2014). The growing senior citizen population puts stress on the United States healthcare system because they are prone to injuries and illnesses (Center for Health Workforce Studies School of Public Health, 2006). If the healthcare demands lead to high workload for medical staff, human performance will decrease which will result in more errors (Teigen, 1994; Yerkes & Dodson, 1908). Medical errors already occur at alarming rates. Past studies have estimated that hundreds of thousands of Americans die each year from medical related errors (James, 2013; Kohn et al., 1999).

The pressures being placed on healthcare systems at a national level are also being experienced at Veterans Affairs (VA) Medical Centers. In late 2014, 10% of VA patients were required to wait more than a month to receive medical treatment (Hoyer & Brook, 2014). In Ohio the wait-time issue is being partially addressed by sending some VA patients to the Medical Center on Wright-Patterson Air Force Base. The 88th Medical Group, who operates the Wright-Patterson Medical Center, is expecting a 30%

patient load increase to inpatient units from the new VA patients (Mort, 2015). To prepare for the patient load increase, the 88th Medical Group is interested in process improvements.

Deming (2000) and Scholtes, Jointer, & Streibel (2003) postulate that over 90% of performance issues in systems can be traced back to poor system design. In healthcare, performance issues include medical errors. To improve medical systems, many hospitals have turned to process improvements. Some process improvement endeavors have used simulations to analyze medical system. Simulations are beneficial because they can test multiple scenarios to understand how changes will influence a system. The current healthcare simulation literature primarily uses time-based metrics like wait times or throughputs (Duguay & Chetouane, 2007; Ferrin et al., 2007; Komashie & Mousavi, 2005). Unfortunately, these studies tend to overlook the mental workload of medical staff which is a critical component of medical systems.

Research Objective

This research was performed to fulfill two objectives. The first objective was to serve as an example of how to quantitatively model the mental workload of medical staff using the Improved Performance Research Integration Tool (IMPRINT) software. Demonstrating how to use IMPRINT to evaluate healthcare systems and potential improvements can help hospitals around that nation. The second objective was to provide specific information to aid in process improvement initiatives for the 88th Medical Group on Wright-Patterson Air Force Base. These objectives are fulfilled using IMPRINT to simulate the mental workload of medical staff in an inpatient unit the

Wright-Patterson Medical Center under current and alternate conditions. After an initial investigation, the researchers propose and test a potential process improvement opportunity.

Baseline Model Evaluation

As explained in Chapter III, the researchers began by modeling the 88th Medical Group's MSU under current conditions. The chapter satisfied the objective of using IMPRINT in novel way to model the mental workload of healthcare staff. It also provided initial information to aid process improvements by evaluating the existing workload differences between staff members.

The IMPRINT outputs indicated large workload differences between staff types. Idle time ranges from 36.76% to 55.05%, average workload ranges from 8.48 to 13.26, percent overload ranges from 2.07% to 6.08% and overload instances ranges from 53.95 to 127.33. Despite the differences, all staff members have high amounts of idle time (over 36.76%). Technicians have the highest amounts of idle time and overload time. The high amount of idle time available and differences in workload metrics between staff members suggests that workload balancing could be beneficial. Balancing workload could most easily be done by working ahead on tasks during free time. Getting ahead on tasks reduced the need to multitask later. However, only some tasks can be worked ahead. Balancing could also be done by sharing some tasks between staff members. If certain tasks could be shared, workload could be balanced by having idle workers help overloaded workers. However, task sharing has limits and does little good if all staff members are busy or idle at the same time.

The IMPRINT model showed a relationship between task complexity and task overload. The most complex tasks have some of the highest overload time because a worker becomes rapidly overloaded if any task is added while a high complexity task is being performed. This effect is even worse when a complex task is also an urgent task. Tasks which must be started immediately tend to become multitasked more often which can lead to overload.

Patient Load Experiment

As discussed in Chapter IV, after analyzing the baseline model, the researchers tested how mental workload is influenced by patient load, in order to assess the impact of future increases in patient demand due to overflow from the Veteran's Affairs medical system. The original IMPRINT model was altered to simulate the MSU under 5 increased patient loads (10%, 20%, 30%, 40, and 50% increases). The alternate models were used to answer the following research question: "What is the impact of an increased patient load on medical staff mental workload in an inpatient unit?" To answer the research question, three investigative questions were created. The answers to each investigative question are provided below.

Investigative Question One

1. What is the relationship between patient load and medical staff mental workload metrics (idle time, average mental workload, overload time)?

The IMPRINT simulation revealed that an increase in patient load decreases idle time, increases average workload, and increases overload time. The relationship between patient load and the workload metrics are approximately linear for all staff types. These

results are intuitive and allow us to conclude that workload metrics are proportionally related to patient load between the baseline patient load and a 50% patient load increase.

Investigative Question Two

2. Which medical staff workers experience the greatest negative impact in mental workload metrics as patient load increases?

Nurses and technicians are the most impacted by patient load increases. Compared to the other staff type, the nurses have the largest decrease in idle time and largest increase in average workload. Similarly, technicians has the largest increase in overload time. Interestingly, the staff type who has the most extreme value for each metric in the baseline model experiences the largest change for those respective metrics. For example, the technicians have the highest overload time under current conditions and the largest increase in overload time at every patient load increase. This effect results in an increased spread in workload metric values for the medical staff members as patient loads increase. In other words, as patient load increases, workload between staff types becomes less balanced.

Investigative Question Three

3. How does patient load influence individual task performance (total task times and overload task times)?

The researchers found the total time and the total time overloaded in a week for each task for each staff member. Overload time infers the quality of task performance. The influence of patient load on total task time depends on task type. “Overhead” tasks which are performed regardless of patient load remain nearly unchanged as patient loads increase. Tasks which are performed for specific patients increase nearly proportionally

with patient load increases. While these findings are trivial, the combination of these tasks for each staff member are insightful. In general, the total amount of time spent on tasks increases as patient loads increase; however, the percentage increase is always less than the patient load percent increase. The shortcoming is because each employee has some number of “overhead” tasks which do not increase as patient load increase. The ratio of “overhead” tasks to patient specific tasks determines the overall percentage increase in work performed by each staff member.

While the overload time of nearly all tasks increase as patient loads increase, there is a difference between urgent and non-urgent tasks. On average, the increases in overload time of urgent tasks is greater than non-urgent tasks. These results infer that the quality of task performance will decrease for all task types; however, urgent tasks will experiences the greatest decrease in performance. Since technicians and shift leaders have many urgent tasks, they are expected to experience the greatest decrease in task performance.

Summary

The patient load experiments provided information on how mental workload will change when the 88th Medical Group begins caring for more VA patients. The linear relationships between patient load and mental workload metrics were as expected. Understanding that nurses and technicians are the most impacted by patient load increases is useful because process improvements should be focused on helping them. Finally, understanding how the different types of tasks are influenced by workload and how staff members with short, frequent, and urgent tasks are more prone to being overload is useful information.

Task Sharing Experiment

After using IMPRINT to evaluate the MSU and answer the three investigative questions, the researchers hypothesized that mental workload metrics (idle time, average workload, and overload time) could be balanced between the medical staff using task sharing. The objective of Chapter V was to evaluate the influence of task sharing on medical staff mental workload metrics using IMPRINT.

To test the hypothesis, "Q2h rounding," was allowed to be shared between all of the staff members. "Q2h rounding" was selected because it is a simple and frequently occurring task. The IMPRINT results indicate that task sharing helps to balance idle time and average workload; however, it makes overload time less balanced. Despite the baseline and alternate model having statistically similar patient loads, the total amount of work performed (evaluated from the average workload metric) increased by 9.5% which was statistically significant. This result indicates that task sharing may help staff members to complete some tasks in a more timely manner which results in better task completion. It is likely that many tasks in the baseline model are being delayed, with some delays lasting until after a patient is discharged and thus eventually being dropped. More timely task completion could have the added benefits of better patient satisfaction and could reduce the number of call lights (urgent calls for assistance made by a patient). Despite the many positive effects of task sharing, the researchers are hesitant to recommend the specific change used in this experiment because it could result in higher error rates due to the negative results on overload time. However, it is likely that additional system changes could fix the overload time issues, resulting in an overall safer and more balanced system.

Recommendations for Action

Given the results of the patient load experiments and the MSU having low error rates under current conditions, the researchers believe that the MSU is capable of safely handling the expected 30% increase in patient load. However, the researchers recommend that patient loads be incrementally increased and the medical staff monitored for overload conditions. Since overload could increase the rate of medical errors, technicians should be most closely monitored due to their initially high overload time and highest expected increase in overload time as patient load increases.

To reduce overloading, the researchers recommend that the MSU works to reduce the complexity of highly complex tasks or ensure that high complexity tasks are not multitasked. Additionally, the researchers recommend that the MSU evaluates and manages the urgency of tasks. Technicians experience high amounts of overload and idle time because they have many urgent tasks, like handling call lights. Reducing the urgency of tasks, or more evenly distributing high urgency tasks amongst staff types, could be beneficial.

The final recommendations are related to workload balancing. Given the surplus of idle time, the researchers recommend MSU management to encourage and allow their staff to work ahead on tasks. Using idle time to work ahead will reduce the need to multitask when unexpected tasks occur and start to build up. Given the mixed results of the task sharing experiment, the researchers are hesitant to recommend the specific task sharing policy used for this research. However, the researchers believe that task sharing should not be ruled out and can be overall beneficial under the right circumstances. If the

MSU was able to fix the overload issue in the task sharing experiment, it would be a beneficial process improvement.

Recommendations for Future Research

This research only scratches the surface on how IMPRINT can be used in healthcare. There are many other ways in which IMPRINT could provide information about a medical system. This research could be continued by testing scenarios in which task complexity or urgency is manipulated. However, the consequences of these changes need to be thoroughly considered. The task sharing experiment could be expanded by sharing other tasks. The existing models could be easily used to evaluate the mental workload metrics of medical staff over the time of day or day of the week. Evaluating mental workload with respect to time could help with staffing level recommendations. Alternatively, an experiment could be performed to evaluate how mental workload metrics change when patient arrival rates are leveled. A final recommendation for future research is to explore the influence of fatigue on task performance.

Final Conclusions

In conclusion, the researchers demonstrated how IMPRINT can be used to model the mental workload of staff in medical systems for the purposes of process improvement. Mental workload has many facets and evaluating each metric simultaneously provides subtle, yet important, insights about the work experienced in a system. Even though this research only focused on idle time, overload time, overload instances, average workload, total task time, and overload task time, there are many other metrics and ways to evaluate the same data. While evaluating the mental workload of

workers in a current system is useful for identify potential issues, using IMPRINT to evaluate future systems is equally beneficial. The results of this research are specific to the 88th Medical Group MSU; however, the methods are generalizable and could be used to model other units or hospitals.

Appendix A – VACP Tables

Table 28 below are the standardized VACP values used in IMPRINT (Alion Science and Technology Corporation, 2015). The scale is derived from Bierbaum, Szabo, and Aldrich, 1989.

Table 28: 7-Channel VACP Scales

Value	Descriptors
	VISUAL
0.0	No Visual Activity
1.0	Visually Register/Detect (detect occurrence of image)
3.0	Visually Inspect/Check (discrete inspection/static condition)
4.0	Visually Locate/Align (selective orientation)
4.4	Visually Track/Follow (maintain orientation)
5.0	Visually Discriminate (detect visual difference)
5.1	Visually Read (symbol)
6.0	Visually Scan/Search/Monitor (continuous/serial inspection, multiple conditions)
	AUDITORY
0.0	No Auditory Activity
1.0	Detect/Register Sound (detect occurrence of sound).
2.0	Orient to Sound (general orientation/attention)
3.0	Interpret Semantic Content (speech, simple, 1-2 words)
4.2	Orient to Sound (selective orientation/attention)
4.3	Verify Auditory Feedback (detect occurrence of anticipated sound)
6.0	Interpret Semantic Content (speech, complex, sentence)
6.6	Discriminate Sound Characteristics (detect auditory differences)
7.0	Interpret Sound Patterns (pulse rates, etc.)
	COGNITIVE
0.0	No Cognitive Activity
1.0	Automatic (simple association)
1.2	Alternative Selection
4.6	Evaluation/Judgment (consider single aspect)
5.0	Sign/Signal Recognition
5.3	Encoding/Decoding, Recall
6.8	Evaluation/Judgment (consider several aspects)
7.0	Estimation, Calculation, Conversion
	FINE MOTOR
0.0	No Fine Motor Activity

2.2 2.6 4.6 5.5 6.5 7.0	Discrete Actuation (button, toggle, trigger) Continuous Adjustive (flight controls, sensor control) Manipulative (tracking) Discrete Adjustment (rotary, vertical thumbwheel, lever position) Symbolic Production (writing) Serial Discrete Manipulation (keyboard entries)
 0.0 1.0 2.0 3.0 3.5 5.0 6.0	<u>GROSS MOTOR</u> No Gross Motor Activity Walking on level terrain Walking on uneven terrain Jogging on level terrain Heavy lifting Jogging on uneven terrain Complex climbing
 0.0 2.0 4.0	<u>SPEECH</u> No speech activity Simple (1-2 words) Complex (Sentence)
 0.0 1.0 2.0 4.0	<u>TACTILE - feeling feedback</u> No tactile activity Alerting Simple discrimination Complex symbolic information

Appendix B – IRB Letters

IRB Exemption Request

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY (AETC)

July 29, 2015

MEMORANDUM FOR AFIT EXEMPT DETERMINATION OFFICIAL

FROM: AFIT/ENV
2950 Hobson Way
Wright Patterson AFB OH 45433-7765

SUBJECT: Request for exemption from human experimentation requirements (32 CFR 219, DoDD 3216.2 and AFI 40-402) for Erich W. Maxheimer Thesis, Analysis of Inpatient Hospital Staff Workload and Patient Load by Means of Discrete-Event Simulation

1. The purpose of this study is to fulfill the requirements of a graduate level systems engineering research project. The research objectives are to create a discrete-event simulation model of the 88th Medical Group, Medical Surgical Unit (MSU) to evaluate staff workload to provide process improvement recommendations. Results will be presented in a forum open to the public through a formal thesis defense and may be published by the academic community should they prove worthy of adding to the existing body of knowledge related to healthcare process improvements or discrete-event simulation involving cognitive workload.

2. This request is based on the Code of Federal Regulations, title 32, part 219, section 101, paragraph (b) (2) Research activities that involve the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless: (i) Information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) Any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

3. The following information is provided to show cause for such an exemption:

a) Equipment and facilities: Observations will be performed through the 88th Medical Group MSU which is a standard inpatient hospital unit. Interviews will be performed in the MSU break room or meeting room.

b) Subjects: Study subjects will be 88th Medical Group hospital staff. It is anticipated that the majority of the subject will be MSU nurses and technicians. The subjects will be selected based on convenience and expertise. The MSU subject pool consists of approximately 35 nurses and 30 technicians and includes male and females, civilian and military, and ages ranging from approximately 20-45 years. Multiple subject samples are necessary for the overall research effort. The first sample will be interviewed to help the researchers build a mental model of the MSU processes. A second sample will be observed working. A third

sample will be interviewed as Subject Matter Experts. Each subject sample will require about 3 subjects. The subjects can be in multiple samples. Subjects will be selected based on availability and experience. Availability is a selection factor because only the 88th Medical Group staff members who are available at the time of observations or interviews will be selected. Experience is a selection factor because it is beneficial to observe and interview subjects with a range of experience levels.

c) Timeframe: The portion of this research effort involving participants of human test subjects is intended to commence only after IRB exemption request approval and conclude after the discrete-event simulation is completed and verified. This process will last 1-4 months during the 2015 calendar year.

d) Data collected: Some of the data used in this study is directly provided by the 88th Medical Group and the remaining data is collected by the researchers. Information provided by the 88th Medical Group are patient record data which includes which units patients were admitted to, the date and time of their admission and discharge, diagnosis, and prescriptions. Dates are the only Protected Health Information that are collected. An explanation of the Protected Health Information and the plan to protect this information is explained in the Healthcare HIPAA Waiver attached. Information collected by the researchers is collected through interviews and observations of the MSU staff. The only personally identifying information collected about the subjects (staff members) is their name, job title, and years of experience. The personally identifying information will be gathered before interviews or observations and will be assigned a random number for data assignment. The Subject Demographic Sheet which records subject personally identifying information will be separate from the data collected during interviews and observations. All other information collected from the subjects is related to the tasks and processes of the MSU. The information will be collected through observations and interviews. Information collected during observations will be recorded in the Observation Data Collection Sheet. The Observation Data Collect Sheet records the tasks performed by a subject over time and includes the time, location, associated patient room number, description, success, and interruption. Information collected during interviews will be recorded in the Task Analysis Data Collection Sheet or the SME Data Collection Sheet. The Task Analysis Data Collection Sheet will record subject responses about the tasks and logic used when caring for patients in the MSU. The SME Data Collection Sheet will record subject estimates on tasks times or probabilities associated with specific tasks. The information collected during observations and interviews are necessary to build a valid discrete-event simulation of the MSU. The names of subjects are needed in case follow up questions are needed from the subject at a later date. The job titles and experience levels of subjects are needed to ensure that information is collected from a wide range of hospital staff.

e) Risks to Subjects: Risk of individual disclosure of private information will be mitigated through the collection of experimental data as mentioned in d) above. Only the researcher will write on any of the data collection sheets to avoid cross correlation of data due to handwriting analysis. While subject physical risk does exist, it is deemed negligible as it does not exceed that of the typical work the hospital staff performs on a daily basis. Physical

risk mitigation to subjects during the observations will be mitigated by not interrupting during task performance and by staying out of the way. The time spent observing subjects is intended to be on the order of 4 hours at a time. The time spent interviewing individual subjects is intended to be on the order of less than 30 minutes (+/- 10 minutes) per interview.

f) Informed consent: All subjects are self-selected to volunteer to participate in the research effort. No adverse action is taken against those who choose not to participate. Subjects are made aware of the nature and purpose of the research, sponsors of the research, and disposition of the research results. A copy of the informed consent document (attached) shall be provided to each participant upon request.

4. If you have any questions about this request, please contact Maj Christina Rusnock, USAF, Ph.D. (primary investigator) – Phone 937-255-3636, ext. 4611; E-mail – christina.rusnock@afit.edu

crusnock@afit.edu
Digitally signed by crusnock@afit.edu
DN: cn=crusnock@afit.edu
Date: 2015.07.30 13:05:04 -04'00'

Maj Christina Rusnock, USAF, Ph.D.
Principal Investigator

Attachments:
1. Informed Consent Document
2. Subject Demographic Sheet
3. Task Analysis Data Collection Sheet
4. Observation Data Collection Sheet
5. SME Data Collection Sheet
6. CITI Training Certificates
7. Curriculum Vitas/Resumes
8. Healthcare HIPAA Waiver Form

Informed Consent Document

Greetings! You are being asked to take part in a research study carried out by Dr. Christina Rusnock and Erich Maxheimer, Air Force Institute of Technology / Systems Engineering and Management (AFIT/ENV). This form explains the study and your part in it if you decide to join. Please read the form carefully; take as much time as desired. Ask the researcher to explain anything you do not understand. You can decide not to join the study. If you do join the study, you can change your mind later or quit at any time without any penalty or loss of services or benefits.

Study Title: Analysis of Inpatient Hospital Staff Workload and Patient Load by Means of Discrete-Event Simulation

Primary Researchers:

Name	Title/Department	E-mail	Telephone
Christina Rusnock, PhD	Assistant Professor of Systems Engineering, AFIT/ENV	christina.rusnock@afit.edu	937.255.3636, x4611
Erich Maxheimer	Master's Student in Systems Engineering, AFIT/ENV	erich.maxheimer.1@us.af.mil	217.871.5664

What is this study about? The purpose of this study is to evaluate the 88th Medical Group, Medical Surgical Unit using discrete-event simulation to evaluate staff workload to provide process improvement recommendations. You are being asked to take part in this study in order to collect data to meet this objective. If you are participating in a SME Data or Task Analysis interview, the researcher will need about 30 minutes of your time – give or take 10 minutes. If you are participating in an Observation, the researcher will need to observe your work activities for about 4 hours – give or take 1 hour. Ask your researcher if you are unsure about which activity you are participating in or if you have any other questions about the study.

What will I be asked to do if I am in this study? Before participating, the researcher will ask you a few demographic questions. If you are participating in an interview, you will be asked additional questions related to the processes of the 88th Medical Group, Medical Surgical Unit. You will either be asked about the steps that you take when working in the MSU or to provide estimates on various metrics like task times. If you are being observed while working, the researcher will ask you to perform your duties as normal. They will take notes on the tasks you perform. They will try to interfere as little as possible during your work and will only ask questions when necessary and at appropriate times. During an observation, be sure to inform the researcher if they are causing any interference or if they need to pause or stop the observation at any time. Interview answers and data collected during observations will be treated by the researcher as For Official Use Only (FOUO) and not shared with anyone outside of the research effort for not only these, but all information you choose to provide as a part of this study.

Are there any benefits to me if I am in this study? You are not expected to benefit directly from participation in this research study. The main benefits of this study will be to help in determining how to improve the 88th Medical Group processes. This could potentially lead to a better work environment or improved patient safety for those in the 88th Medical Group.

Are there any risks to me if I am in this study? Because this research requests your demographics and information that you provide about the Medical Surgical Unit processes, some of your response might be considered sensitive or cause discomfort. For this reason you may refuse to answer any question at any time, and likewise may opt out of the study at any time without question. It is also important to note that it might still be possible for a reader of the final written product to attribute results to a given individual and/or organization. You

will be given an opportunity to review information provided and make a reasoned judgment of the risks of divulging such information.

Will my information be kept private? The data for this study will be kept confidential to the extent allowed by federal and state law. No published results will identify you, and your name will not be associated with the findings. Under certain circumstances, information that identifies you may be released for internal and external reviews of this study. The digital file containing the data collection as a result of your participation, as well as the study write-up will be secured on a password-protected computer assigned to the researcher. Additionally, data collected may be released for future studies. If released it will be sanitized and anonymized as required to ensure that no personally identifiable information (PII) is present. Your information will only be released, if requested, to authorize members of the AFIT Institutional Review Board (IRB), to ensure research compliance with federal and state law. Your information will not be released to any other entity. The results of this study may be published or presented at professional meetings, but the identities of all research participants will remain anonymous. The data for this study will be kept for three years, as required by AFIT policy, after which time the digital file containing all personal data will be destroyed and all remaining data will remain completely anonymized.

Are there any costs or payments for being in this study? There will be no costs or payments to you for taking part in this study.

Who can I talk to if I have questions? If you have questions about this study or the information in this form, please contact the researcher using the contact information provided above. If you have questions about your rights as a research participant, or would like to report a concern or complaint about this study, please contact the WPAFB Institutional Review Board at (937) 255-3636, x4543 or e-mail HumanSubjects@afit.edu, or regular mail at: Wright Research Site IRB, 711 HPW/IR, 2245 Monahan Way, Wright-Patterson AFB, OH 45433

What are my rights as a research study volunteer? Your participation in this research study is completely voluntary. You may choose not to be a part of this study. There will be no penalty to you if you choose not to take part. You may choose not to answer specific questions or to stop participating at any time.

What does my signature on this consent form mean? Your signature on this form means that: a) you understand the information given to you, b) you have been able to ask the researcher questions and state any concerns, c) the researcher has responded to your questions and concerns, d) you believe you understand the research study and the potential benefits and risks involved.

Statement of Consent: I give my voluntary consent to take part in this study. I will be given a copy of this consent document for my records.

Signature of Participant	Printed Name of Participant	Date

Statement of Person Obtaining Informed Consent: I carefully explained to the person taking part in the study what he or she can expect. I certify that when this person signs this form, to the best of my knowledge, he or she understands the purpose, procedures, potential benefits, and potential risks of participation. I also certify that he or she: a) speaks the language used to explain this research, b) reads well enough to understand this form, c) does not have any problems that could make it hard to understand what it means to take part in this research.

Signature of Researcher	Printed Name of Researcher	Date

Subject Demographic Sheet

Subject Demographic Sheet

Note: Only the research Investigators will ever view or fill out this form.

Subject Number	Name	Job Title	Years of Experience
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			
16			
17			
18			
19			
20			

Task Analysis Data Collection Sheet

Task Analysis: Verbal Protocol Form

Subject Number__________

Mentally "walk through" and explain the tasks you would perform during a patient's admission process. Include potential variations in the process and logic used when transitioning between tasks.

Mentally "walk through" and explain the tasks you would perform caring for a patient during their stay. Include potential variations in the process and logic used when transitioning between tasks.

Mentally "walk through" and explain the tasks you would perform during a patient's discharge process. Include potential variations in the process and logic used when transitioning between tasks.

Mentally "walk through" and explain the tasks you would perform during a shift in the MSU that is not specifically associate with patient care. Include potential variations in the process and logic used when transitioning between tasks.

Observation Data Collection Sheet

Date:		Subject Number				
Notes:						
Start Time	Location		Details			
	Start	End	Patient Room Number	Description of Task	Success?	Interruption?

SME Data Collection Sheet

SME Data Collection Sheet

Subject Number__________

The following table is used to gather Subject Matter Expert Data on specific tasks or metrics included in the discrete-event simulation model. For a given task or metric, the table include spaces for the SMEs estimates on the absolute low, most common, and absolute high values.

Task/Metric	Absolute Min	Mode	Absolute Max

IRB Exemption Approval

DEPARTMENT OF THE AIR FORCE
AIR FORCE INSTITUTE OF TECHNOLOGY
WRIGHT-PATTERSON AIR FORCE BASE OHIO

10 August 2015

MEMORANDUM FOR MAJ CHRISTINA RUSNOCK

FROM: William A. Cunningham, Ph.D.
AFIT IRB Research Reviewer
2950 Hobson Way
Wright-Patterson AFB, OH 45433-7765

SUBJECT: Approval for exemption request from human experimentation requirements (32 CFR 219, DoDD 3216.2 and AFI 40-402) for your study "Analysis of Inpatient Hospital Staff Workload and Patient Load by Means of Discrete-Event Simulation".

1. Your request was based on the Code of Federal Regulations, title 32, part 219, section 101, paragraph (b) (2) Research activities that involve the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless: (i) Information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) Any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

2. Your study qualifies for this exemption because you are not collecting sensitive data, which could reasonably damage the subjects' financial standing, employability, or reputation. Further, the demographic data you are utilizing and the way that you plan to report it cannot realistically be expected to map a given response to a specific subject.

3. This determination pertains only to the Federal, Department of Defense, and Air Force regulations that govern the use of human subjects in research. Further, if a subject's future response reasonably places them at risk of criminal or civil liability or is damaging to their financial standing, employability, or reputation, you are required to file an adverse event report with this office immediately.

William Cunningham

WILLIAM A CUNNINGHAM, PH.D.
AFIT Exempt Determination Official

Appendix C – Input Data Modeling

The IMPRINT model required input data on length of stay, patient arrival rate, task durations, and other probabilities. The first two metrics were created using electronic hospital records. The remaining records were collected using SME estimates. Details on each metric is provided below.

Length of Stay Data

One month of Essentris records were used to create a length of stay distribution using Arena's Input Analyzer. In order to improve the fit, the data was separated into two distributions by separating three outliers from the main group of data points. Arena's Input Analyzer fit a lognormal distribution (mean=2.44 days, standard deviation=2.3 days) as shown in Figure 12. The Chi Square Test provides a P-value of 0.036 and the Kolmogorov-Smirnov Test provides a P-value of 0.0712. Despite having a poor goodness of fit, the distribution was used because it was the most accurate representation of the MSU length of stay metric available to the researchers. The three outliers were accounted for using a rectangular distribution (mean=17.51 days, min=15 days) which is drawn from 1.2% of the time. The remaining 98.8% of the time is drawn from the lognormal distribution.

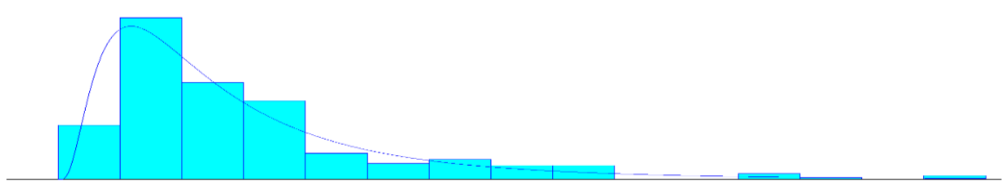

Figure 12: Length of Stay Distribution

Arrival Rate Data

The arrival rate input data was collected from the one month of Essentris data. A Tukey's Test was performed to determine which days and times should be grouped into similar arrival rates. Using Table 29 below, it was determined that the IMPRINT model should have four different arrival rates based on the following groups:

1. Monday, Tuesday, and Wednesday
2. Thursday and Friday
3. Saturday and Sunday
4. all nights

Table 29: Essentris Records Patient Arrivals Over Time

Grouping Information Using the Tukey Method and 95% Confidence						
Weekday	N	Mean	Grouping			
Monday Day	4	12.25	A			
Tuesday Day	4	11	A	B		
Wednesday Day	4	10.25	A	B		
Friday Day	4	7.75	A	B	C	
Thursday Day	4	6		B	C	D
Sunday Day	4	2.75			C	D
Saturday Day	4	2.25			C	D
Wednesday Night	4	1.75				D
Monday Night	4	1.75				D
Tuesday Night	4	1.5				D
Thursday Night	4	1.25				D
Saturday Night	4	1.25				D
Friday Night	4	1.25				D
Sunday Night	4	1				D
Means that do not share a letter are significantly different.						

With the four groups established, the Essentris records were used to create rectangular distributions of the time between patients. The data used to create the

distributions and the outputs from four model runs which verify the model arrival rates are shown in the Table 30. The arrival rates, along with the length of stay metric, are the two main factors influencing the patient throughput of the model. The model throughput is validated using the WeeklyDischarge metric in Appendix F – Baseline Model Validation.

Table 30: Patient Arrivals over Time

	(Essentris Records, 4 weeks)				Four IMPRINT Runs			
Time	**S/S**	**M/T/W**	**Th/F**	**Night**	**S/S**	**M/T/W**	**Th/F**	**Night**
	1	5	5	0	1	4	6	0
	1	6	6	0	1	6	6	0
	2	8	6	0	1	6	6	0
	3	9	6	0	1	6	6	1
	3	10	7	0	3	7	7	1
	4	10	7	0	4	7	7	1
	4	10	9	0	4	7	8	1
	4	10	10	0	5	8	11	1
		11		1		8		1
		11		1		12		1
		13		1		12		1
		13		1		14		1
				1				1
# Patients				1				1
				1				1
				1				1
				1				1
				1				1
				1				1
				1				1
				1				1
				1				2
				2				2
				2				2
				2				2
				2				2
				3				2
				3				3
Mean	2.75	9.67	7.00	1.00	2.50	8.08	7.13	1.18
Std Dev	1.28	2.42	1.69	0.86	1.69	3.00	1.73	0.67

SME Task Time Estimates

SME estimates were collected from six different subjects. Each subject only provided estimates for metrics that they had experience with. Time restrictions during SME interviews also limited the number of metrics which some subjects could provide estimates for. For each metric, the minimum of the minimum, the maximum of the maximum, and the average of the mode was used as the combined SME values. These values were used as triangular distributions in the IMPRINT model. The complete set of estimates are provided in Table 31 below.

Table 31: Subject Matter Expert (SME) Estimates

SME Data					Combined SME Data			SME: 2			SME: 3			SME: 4			SME: 5			SME: 6			SME: 7		
Input Data Name	Description	Data Type	Staff Type	Unit	Min of Min	Avg Mode	Max of Max	Min	Mode	Max	Min	Mode	Max	Min	Mode	Max	Min	Mode	Max	Min	Mode	Max	Min	Mode	Max
Call Light Frequency	Time between call lights for a patient	Arrival Time	All	min	10.00	96.00	1440.00	14.4	120	1440	12	96	1440	-	-	-	10	48	1440	12	120	1440	-	-	-
Call Light Durations	Duration to handle call light and any necessary interventions	Process Time	All	min	0.25	7.50	60.00	0.25	5	45	1	5	60	-	-	-	3	10	60	1	10	30	-	-	-
Nurse Call Light Probability	Probabilities of nurse handling call light	Probability	Nurse	%	-	28.80	-	-	29	-	-	30	-	-	-	-	-	35	-	-	35	-	-	15	-
Technician Call Light Probability	Probabilities of technician handling call light	Probability	Tech	%	-	66.80	-	-	70	-	-	65	-	-	-	-	-	60	-	-	55	-	-	84	-
Charge Nurse Call Light	Probabilities of charge nurse handling call light	Probability	Charge Nurse	%	-	4.40	-	-	1	-	-	5	-	-	-	-	-	5	-	-	10	-	-	1	-
Nurse Change Shift Duration	Duration for a nurse to change shift	Process Time	Nurse	min	10.00	26.67	60.00	10	30	60	-	-	-	-	-	-	10	20	30	10	30	40	-	-	-
Tech Change Shift Duration	Duration for a technician to change shift	Process Time	Tech	min	5.00	8.50	15.00	5	10	15	-	-	-	-	-	-	-	-	-	-	-	-	5	7	12
CN Change Shift Duration	Duration for a charge nurse to change shift	Process Time	Charge Nurse	min	15.00	30.00	60.00	15	30	60	25	40	60	-	-	-	-	-	-	15	20	30	-	-	-
Shift Leader Change Shift Duration	Duration for a shift leader to change shift	Process Time	Shift Leader	min	10.00	16.67	30.00	10	20	30	-	-	-	10	15	25	-	-	-	-	-	-	10	15	20
Room Prep Duration	Duration to prepare room before patient arrival	Process Time	Nurse/Tech	min	1.00	5.20	10.00	5	7	10	5	7	10	-	-	-	5	7	10	2	2	5	1	3	5
Strip Room Duration	Duration to strip room after patient discharges	Process Time	Nurse/Tech	min	3.00	6.25	15.00	5	7	10	5	7	15	-	-	-	5	7	10	3	4	5	-	-	-
Receive Report Duration	Duration for nurse to receive report call	Process Time	Nurse	min	3.00	9.75	20.00	10	15	20	4	10	15	-	-	-	5	7	10	3	7	10	-	-	-
Preview Patient Info Duration	Duration for nurse to preview orders/records	Process Time	Nurse	min	0.00	3.75	10.00	1	3	5	2	5	10	-	-	-	0	5	10	1	2	3	-	-	-
Admission Notes Duration	Duration for nurse to fill out admission notes and perform necessary actions	Process Time	Nurse	min	7.00	12.50	25.00	-	-	-	-	-	-	-	-	-	7	10	25	10	15	20	-	-	-
Perform Admission Orders Duration	Duration for nurse to perform all admission orders	Process Time	Nurse	min	5.00	28.75	90.00	10	30	60	15	35	90	-	-	-	5	20	30	10	30	60	-	-	-
Administering Meds Duration	Duration to administer medication (includes pills, shots, IV, etc.)	Process Time	Nurse	min	5.00	12.33	30.00	5	12	20	-	-	-	-	-	-	5	10	15	10	15	30	-	-	-
6 Hr Med Distribution	Probability that a patient needs meds every 6 hours	Probability	-	%	-	31.25	-	-	35	-	-	20	-	-	-	-	-	45	-	-	25	-	-	-	-
12 Hr Med Distribution	Probability that a patient needs meds every 12 hours	Probability	-	%	-	68.75	-	-	65	-	-	80	-	-	-	-	-	55	-	-	75	-	-	-	-
Q2h Rounding Duration	Duration for nurse or technician to Q2h rounds for a patient	Process Time	Nurse/Tech	min	0.25	7.00	25.00	3	7	20	2	10	25	2	5	10	3	5	15	0.25	5	15	5	10	20
Full Assessment Duration	Duration for nurse to make full assessment	Process Time	Nurse	min	8.00	15.00	30.00	8	13	20	10	20	30	-	-	-	10	12	15	10	15	20	-	-	-
Vitals, I/Os, Neuro Duration	Duration to perform Vitals, I/Os, Neuro	Process Time	Tech	min	3.00	8.40	20.00	5	10	20	7	10	15	-	-	-	5	7	10	3	5	10	5	10	20
No Test Percentage	Percentage of patients who do not need test done on a given day	Probability	-	%	-	60.00	-	-	70	-	-	70	-	-	-	-	-	50	-	-	50	-	-	-	-
One Test Percentage	Percentage of patients who need 1 test done on a given day	Probability	-	%	-	18.75	-	-	20	-	-	15	-	-	-	-	-	20	-	-	20	-	-	-	-
Two Test Percentage	Percentage of patients who need 2 test done on a given day	Probability	-	%	-	12.50	-	-	5	-	-	10	-	-	-	-	-	20	-	-	15	-	-	-	-
Three or More Test Percentage	Percentage of patients who need 3+ tests done on a given day	Probability	-	%	-	8.75	-	-	5	-	-	5	-	-	-	-	-	10	-	-	15	-	-	-	-
Duration of Test Transport	Duration for technician to transport patient to test and from test	Process Time	Tech	min	4.00	9.00	14.00	5	7	10	-	-	-	-	-	-	4	8	10	10	12	14	6	9	12
Test Duration	Duration for patient to be at test (only done during day shift)	Process Time	-	min	5.00	50.00	120.00	30	45	60	-	-	-	-	-	-	30	45	60	5	60	120	-	-	-
No Lab Percentage	Percentage of patient do not need a lab drawn by MSU staff on a given day	Probability	-	%	-	50.00	-	-	50	-	-	-	-	-	-	-	-	50	-	-	50	-	-	-	-
One Lab Percentage	Percentage of patient need 1 lab drawn by MSU staff on a given day	Probability	-	%	-	25.00	-	-	20	-	-	-	-	-	-	-	-	25	-	-	30	-	-	-	-
Two Labs Percentage	Percentage of patient need 2 labs drawn by MSU staff on a given day	Probability	-	%	-	18.33	-	-	20	-	-	-	-	-	-	-	-	20	-	-	15	-	-	-	-
Three Labs Percentage	Percentage of patient need 3 labs drawn by MSU staff on a given day	Probability	-	%	-	6.67	-	-	10	-	-	-	-	-	-	-	-	5	-	-	5	-	-	-	-
Duration of Lab Collection and Transport	Duration to collect lab and transport to laboratory	Process Time	Nurse/Tech	min	8.00	14.00	40.00	10	12	15	-	-	-	-	-	-	10	20	40	-	-	-	8	10	15
Nurse Lab Collection Probability	Percentage of time that the nurse draws lab	Probability	Nurse	%	-	40.00	-	-	45	-	-	-	-	-	-	-	-	50	-	-	40	-	-	25	-
Technician Lab Collection Probability	Percentage of time that the techician draws lab	Probability	Tech	%	-	60.00	-	-	55	-	-	-	-	-	-	-	-	50	-	-	60	-	-	75	-
Remove Invasive Devices Duration	Duration for techician to remove invasive devices before discharge	Process Time	Tech	min	3.00	5.50	10.00	3	5	10	-	-	-	-	-	-	5	7	10	3	5	10	4	5	8
Prepare/Print Discharge Papers Duration	Duration to prepare/print papers for dishcarge	Process Time	Nurse	min	2.00	5.33	15.00	6	7	15	-	-	-	-	-	-	3	4	5	2	5	10	-	-	-
Prepare PT for Discharge Duration	Duration to review forms with patient and prepare for discharge	Process Time	Nurse	min	3.00	7.33	20.00	6	7	15	-	-	-	-	-	-	5	10	20	3	5	15	-	-	-
Perform Discharge Orders Duration	Duration to perform discharge orders	Process Time	Nurse	min	0.00	10.00	20.00	0	10	20	-	-	-	-	-	-	0	5	10	5	15	20	-	-	-
Discharge from Unit Duration	Duration to physically discharge out of MSU	Process Time	Nurse/Tech	min	5.00	11.75	25.00	5	10	25	-	-	-	-	-	-	10	15	20	5	10	15	10	12	15
Nurse Discharge PT Probability	Percentage of time that nurse discharged patient	Probability	Nurse	%	-	41.25	-	-	40	-	-	-	-	-	-	-	-	50	-	-	50	-	-	25	-
Technician Discharge PT Probability	Percentage of time that techician discharged patient	Probability	Tech	%	-	58.75	-	-	60	-	-	-	-	-	-	-	-	50	-	-	50	-	-	75	-
Close/Turn-in Records Duration	Duration for nurse to close out patient records and turn in to admin	Process Time	Nurse	min	3.00	7.00	15.00	3	4	5	-	-	-	-	-	-	5	7	10	5	10	15	-	-	-
Time between Dischare Orders and Discharge	Time between discharge orders and patient physically discharging	Process Time	-	min	-	43.33	-	-	60	-	-	-	-	-	-	-	-	40	-	-	30	-	-	-	-
Assign Patient to Room/Nurse Duration	Duration for charge nurse to find and assign patient to room and nurse	Process Time	Charge Nurse	min	2.00	11.50	20.00	2	15	20	-	-	-	-	-	-	-	-	-	4	8	10	-	-	-
Assign Patient to Technician Duration	Duration for shift leader to find and assign patient to technician	Process Time	Shift Leader	min	1.00	4.00	10.00	1	3	7	-	-	-	1	5	10	-	-	-	-	-	-	1	4	5
Discharge Record Update Duration	Duration to update board/journal/WMSN after patient dishcarge	Process Time	Charge Nurse	min	4.00	11.00	20.00	15	17	20	-	-	-	-	-	-	-	-	-	4	5	10	-	-	-
Bed Meeting Duration	Duration for bed meeting in ED conference room (0745, M-F)	Process Time	Charge Nurse	min	5.00	12.50	20.00	-	-	-	10	15	20	-	-	-	-	-	-	5	10	20	-	-	-
Internal Med Meeting Duration	Duration for charge nurse to meet with discharge planner (0830 M-F)	Process Time	Charge Nurse	min	15.00	25.00	45.00	-	-	-	25	30	45	-	-	-	-	-	-	15	20	25	-	-	-
72 Hour Callback Duration	Duration to complete 72 hr callback during shift per patient during day shift	Process Time	Charge Nurse	min	3.00	6.00	10.00	5	7	10	-	-	-	-	-	-	-	-	-	3	5	7	-	-	-
Restock Med Room Duration	Duration to restock med room each shift	Process Time	Charge Nurse	min	8.00	12.50	20.00	10	15	20	-	-	-	-	-	-	-	-	-	8	10	15	-	-	-
Clean Nurse Station Duration	Duration for charge nurse to Cavi-Wipe Nurse Station	Process Time	Charge Nurse	min	5.00	10.00	15.00	-	-	-	5	10	15	-	-	-	-	-	-	8	10	15	-	-	-
Visitor/Call Frequency (Day)	Time between visitors/calls during day (0600-2200)	Arrival Time	-	min	0.10	9.00	20.00	0.1	10	20	-	-	-	-	-	-	-	-	-	2	8	15	-	-	-
Visitor/Call Frequency (Night)	Time between visitors/calls during night (2200-0600)	Arrival Time	-	min	5.00	25.00	60.00	5	20	30	-	-	-	-	-	-	-	-	-	10	30	60	-	-	-
Help Call/Visitor Duration	Duration to handle calls/visitors	Process Time	Charge Nurse	min	0.10	1.00	10.00	0.1	0.5	10	0.25	1.5	10	-	-	-	-	-	-	0.1	1	10	-	-	-
Sunday Night Charge Nurse Tasks Duration	Total duration to complete Sunday night tasks	Process Time	Charge Nurse	min	20.00	45.00	80.00	-	-	-	40	60	80	-	-	-	-	-	-	20	30	50	-	-	-
Sunday Night Shift Leader Tasks Duration	Total duration to complete Sunday night tasks	Process Time	Shift Leader	min	10.00	22.50	60.00	-	-	-	-	-	-	25	30	60	-	-	-	-	-	-	10	15	30
Charge Rounds Duration	Duration for charge nurse to round and perform minor misc tasks	Process Time	Charge Nurse	min	20.00	70.00	120.00	-	-	-	50	90	120	-	-	-	-	-	-	20	50	90	-	-	-
Restock Rooms Duration	Duration for shift leader to restock patient and supply rooms	Process Time	Shift Leader	min	10.00	22.50	45.00	-	-	-	-	-	-	25	30	45	-	-	-	-	-	-	10	15	20
Misc Cleaning Duration	Duration to clean patient rooms and breakroom	Process Time	Shift Leader	min	10.00	22.50	45.00	-	-	-	-	-	-	25	30	45	-	-	-	-	-	-	10	15	20
Shift Leader Misc. Checks	Duration for Shift Ldr to check O2, crash carts, refrig temps, etc.	Process Time	Shift Leader	min	10.00	17.50	25.00	-	-	-	-	-	-	10	20	25	-	-	-	-	-	-	10	15	20

Appendix D – Baseline Model

Table 32 explains each task in the IMPRINT model. The tasks in the table are shown in the figures in the Task Networks Figures section. The operator is the staff member who performs the task. The task logic includes information such as the type of input data used for the tasks, release conditions, paths, and VACP values. The IMPRINT variable table lists each variable used in the model and explains what they are used for. The Snapshots tables explains each snapshot used in the model. Snapshots are custom outputs that the IMPRINT model generates.

Table 32: Model Task Logic

Tasks	Operator	Logic
All nurse, technician, charge nurse, and shift leader tasks	All	When these tasks start, the Nurse#Busy, Tech#Busy, CNBusy, or ShiftLdrBusy variables are increased by 1 to indicate that the operator is "busy." The variable is decrease by 1 when the task is completed.
0 START (Sunday 0000)	-	The model starts on Sunday at 0000.
101 Random Delay	-	This task decides on the arrival rate of phone calls and visitors based on the day or night time. It uses the SME estimate "Visitor/Call Frequency (Day)" and "Visitor/Call Frequency (Night)" Each time the task ends, it restarts and also send an entity to "98 Help Visitors/Phone Calls"
98 Help Visitors/Phone Calls	Charge Nurse	This task models the charge nurse helping visitors and taking phone calls. The duration uses the SME estimate "Help Call/Visitor Duration." The VACP value=12. The task starts immediately because visitors and phone calls must be helped quickly.
18 Timer (3 wk)	-	This task acts as the model timer by running for 1814400 seconds and then halts the model.
120 Day of Week	-	This task runs for 24 hours and then restarts itself. Every time that the task ends, it changes the DayOfWeek

		variable to keep track of the day of the week.
124 S/S	-	This task is used to generate a new patients on Saturdays and Sundays during the day. The duration of the task is the time between patients and is built from the arrival rates in the Essentris records. Every time that the task ends, it restarts by sending a new entity to itself, so it is always in progress. The task only send an entity, which represent a new patient, to "17 New Patient" if DayorNight equals 1 and DayOfWeek equals 0 or 6. Each new patient is tagged in this task to keep track of the patient throughout the model.
122 MTW	-	This task is used to generate a new patients on Monday, Tuesday, and Wednesday during the day. The duration of the task is the time between patients and is built from the arrival rates in the Essentris records. Every time that the task ends, it restarts by sending a new entity to itself, so it is always in progress. The task only send an entity, which represent a new patient, to "17 New Patient" if DayorNight equals 1 and DayOfWeek equals 1, 2, or 3. Each new patient is tagged in this task to keep track of the patient throughout the model.
121 TH/F	-	This task is used to generate a new patients on Thursday and Friday during the day. The duration of the task is the time between patients and is built from the arrival rates in the Essentris records. Every time that the task ends, it restarts by sending a new entity to itself, so it is always in progress. The task only send an entity, which represent a new patient, to "17 New Patient" if DayorNight equals 1 and DayOfWeek equals 4 or 5. Each new patient is tagged in this task to keep track of the patient throughout the model.
123 Night	-	This task is used to generate a new patients during the night. The duration of the task is the time between patients and is built from the arrival rates in the Essentris records. Every time that the task ends, it restarts by sending a new entity to itself, so it is always in progress. The task only send an entity, which represent a new patient, to "17 New Patient" if DayorNight equals 0. Each new patient is tagged in this task to keep track of the patient throughout the model.
17 New Patient	-	This task is used to send new patients into the MSU (if BedUtilization<=38) or turn them away if the MSU is at capacity by having more than 38 patients

		(BedUtilization>38).
132 Turned Away Patient	-	This task is used in the TurnedAwayPatients snapshot. Every time that an entity starts the task, the time is recorded and the entity goes no further.
23 Assign Patient to Room/Nurse	Charge Nurse	This task represent the time spent assigning new patients to a nurse and room. The task duration uses the SME estimate "Assign Patient to Room/Nurse Duration" and has a VACP value=16.8. The NursePatientLoad for each nurse is compared to determine which nurse to assign a patient. The nurse with the lowest patient load and lowest number, if there is a tie, is sent the patient. Once a nurse is selected, their NursePatientLoad value is increased by 1. Also the Nurse#Clock is set to the Clock value as part of the Nurse#AveragePatientLoad snapshot. The Admit variable is increased by 1. The BedUtilization variable is increased by 1. The PatientInfo[Entity.Tag,3] is updated to indicate the medication schedule for the new patient using the SME estimate "6 Hr Med Distribution" and "12 Hr Med Distribution." The task starts immediately because it is an urgent task that needs to be done before the patient arrives.
70-75 Nurse#	-	The functions include the task network for each of the 6 nurses. The only difference between the functions are the operators. Each function is specifically used for its corresponding nurse.
45 Update Board/journal/WMSN	Charge Nurse	This task represents the work performed by the charge nurse right after a patient is discharged. The charge nurse updates the patient board, their journal, and the WMSN. The task is only started when the charge nurse is free (CNBusy==0) because it can be delayed with little consequence. The VACP value=13.3 and the task duration uses the SME estimate "Discharge Record Update Duration."
24 Assign Patient to Tech	Shift Leader	This task represents the work performed by the shift leader right after they are informed of a new patient by the charge nurse. It involves selecting, finding, and informing a technician for each new patient. The task uses the TechPatientLoad to determine which technician is assigned a patient. The technician with the lowest patient load and lowest number, if there is a tie is selected. The shift leader also cares for patients so they can be assigned the patient if they have 1 fewer patients than all other technicians. Once a technician is selected,

		their TechPatientLoad is increased by 1 and the Tech#Clock is set equal to the Clock as part of the Tech#AveragePatientLoad snapshot. The task has a VACP value=14.3 and the duration uses the SME estimate "Assign Patient to Technician Duration." The task starts immediately because it is an urgent task that needs to be done before the patient arrives.
77-80 Technician#	-	The functions include the task network for each of the 4 technicians. The only difference between the functions are the operators. Each function is specifically used for its corresponding technicians.
9 Shift Leader	-	The functions include the task network for the shift leader. The function is just like the technician functions expect the tasks are performed by the shift leader.
83 Patient Arrival	-	This task is used to indicate that the patient has arrived to the MSU. It can only start when the assigned nurse has received the report for the patient (PatientInfo[Entity.Tag,2]==1]. When the task ends, PatientInfo[Entity.Tag,1] is set to 1 to show that the patient has arrived. The task sends and entity to "102 Call Light Delay" to start the possibility that the patient will have a call light. It also sends an entity to "85 LOS" to start the length of stay clock for the patient.
85 LOS	-	The duration of this task determines how long the patient will be in the MSU. The duration uses the Length of Stay distribution built from the Essentris records minus 2599.8 seconds which is the SME estimate "Time between Discharge Orders and Discharge." The SME estimate is subtract to account for the duration of the tasks which must be completed after discharge orders are received and the patient is physically discharged. When the task is completed, an entity is sent to "114 D/C Orders."
114 D/C Order	-	This task simply indicates that discharge orders are received by making PatientInfo[Entity.Tag,1] equal to 2.
84 PT Discharged	-	This task is started when the patient is physically discharged (PatientInfo[Entity.Tag,1]==3]). When this occurs, BedUtilization is reduced by 1. If the model is in the final week (Clock>=1209600) the WeeklyDischarge is increased by 1. An entity is sent to "119 72hr Delay."
119 72hr Delay	-	The task is a clock that lasts for 72 hours. When it is completed, it sends and entity to "96 72 Hour Callbacks" so that the charge nurse can make a callback.

96 72 Hour Callbacks	Charge Nurse	After the 72 hour delay, the charge nurse calls back the patient to make answer any questions they may have and remind them of important information regarding their illness. The task only starts if the charge nurse is free because it is not time critical. Also, it only starts during the day so that the patient is awake for the call. The VACP value=19.3 and the task duration uses the SME estimate "72 Hour Callback Duration."
999 END	-	When an entity reaches this task, all other entities with the same tag representing a patient are removed from the model.
130 16 Hr Delay	-	After the start of the model, this task is used as a delay for the "104 Sunday Night" task. The task duration is exactly 16 hours.
105 Sunday Night	-	This task starts during the start of each Sunday night shift. The task sends an entity to "99 Nurse, Q Sunday Night Tasks" and "100 Tech, Q Sunday Night Tasks."
129 Week Delay	-	This task is used to delay the "105 Sunday Night" task by a week. The task duration is exactly 168 hours long.
99 Nurse, Q Sunday Night Tasks	Charge Nurse	This task represent the charge nurse tasks performed during the Sunday night shift which includes cleaning the breakroom microwave and coffee maker, the doing the PYXIS narcotic inventory, and cleaning and defrosting the med refrigerator. The task is only started when the charge nurse is not busy (CNBusy==0). The VACP value=10.2 and the duration uses the SME estimate "Sunday Night Charge Nurse Tasks Duration".
100 Tech, Q Sunday Night Tasks	Shift Leader	This task represent the shift leader tasks performed during the Sunday night shift which includes cleaning the breakroom and patient refrigerators, the water and ice dispenser, eye wash station, crash cart, storage shelves as well as CBG and EKG tasks. The task is only started when the shift leader is not busy (ShiftLdrBusy==0). The VACP value=10.2 and the duration uses the SME estimate "Sunday Night Shift Leader Tasks Duration."
69 6 Hr Delay	-	After the start of the model, this task is used as a delay for the shift change and shift change tasks which occur at 06:00 and 22:00. The task duration is exactly 21600 seconds.
125 Shift Change	-	This function contains each staff members shift change task and start at exactly 06:00 and 22:00.
62 Shift Change	-	This is started at exactly 06:00 and 22:00 and increases

(6AM/PM)		the Shift variable by 1.
66 12 Hr Delay	-	This task is has a duration of exactly 43200 seconds and acts as a 12 hour delay for the shift change tasks.
128 1.25 Hr Delay	-	This task is exactly 1.25 hours long and is a delay for the "110 Clean Nurse Station (0715/1915)" task.
110 Clean Nurse Station (0715/1915)	Charge Nurse	Task which represent the charge nurse cleaning the work station near the start of a new shift. The task is only started when the charge nurse is not busy (CNBusy==0). VACP value=8.6 and the task duration uses the SME estimate "Clean Nurse Station Duration."
117 Day (0600-2200)	-	This task keeps track of the daytime in the MSU which is defined as 06:00 to 22:00. The task lasts exactly 16 hours and while the task is in progress, DayorNight=1.
118 Night (2200-0600)	-	This task keeps track of the nighttime in the MSU which is defined as 22:00 to 06:00. The task lasts exactly 8 hours and while the task is in progress, DayorNight=0.
126 1.75 Hr Delay	-	This task is exactly 1.75 hours long and is a delay for the "95 Bed Meeting (0745,M-F)" task.
95 Bed Meeting (0745, M-F)	Charge Nurse	This task represents the bed meeting which the charge nurse attends in the morning. The VACP value=18.5 and the task duration uses the SME estimate of "Bed Meeting Duration." The task starts exactly at 0745.
127 2.5 Hr Delay	-	This task is exactly 2.5 hours long and is a delay for the "108 Internal Med Meeting (08:30,M-F)" task.
108 Internal Bed Meeting (830, M-F)	Charge Nurse	This task represents the internal med meeting which the charge nurse attends in the morning. The VACP value=18.5 and the task duration uses the SME estimate of "Internal Med Meeting Duration." The task starts exactly at 08:30.
106 1/Shift Tasks	-	This task send an entity to each task which happens once per shift.
97 Restock Med Room	Charge Nurse	This task represents the charge nurse restocking the med room which is done once per shift. The task only starts when the charge nurse is not busy (CNBusy==0). The VACP value=10.2 and the duration of the task uses the SME estimate "Restock Med Room Duration."
107 Charge Rounds	Charge Nurse	This task represents the charge nurse charge rounds which is done once per shift. The task only starts when the charge nurse is not busy (CNBusy==0). The VACP value=10.2 and the duration of the task uses the SME estimate "Charge Rounds Duration."

111 Restock PT & Supply Rooms	Shift Leader	This task represents the shift leader tasks of restocking patient and supply rooms which is done once per shift. The task only starts when the shift leader is not busy (ShiftLdrBusy==0). The VACP value=10.2 and the duration of the task uses the SME estimate "Restock Rooms Duration."
131 5 Hr Delay	-	This task is exactly 5 hours long and is a delay for the "112 Misc Cleaning (PTs rooms/trays, Breakroom)" task.
112 Misc Cleaning (PTs rooms/trays, Breakroom)	Shift Leader	This task represents the shift leader cleaning tasks which are done once per shift. The task only starts when the shift leader is not busy (ShiftLdrBusy==0). The VACP value=10.2 and the duration of the task uses the SME estimate "Misc Cleaning Duration."
113 Shift Ldr Misc Checks	Shift Leader	This task represents the shift leader checks of the O2, crash carts, and refrigerator temps which happen once per shift. The task starts immediately at the start of a shift. The VACP value=10.2 and the duration of the task uses the SME estimate "Shift Leader Misc. Checks."
102 Call Light Delay	-	This task generates call lights for each patient in the MSU. The task can only start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1). The duration of the task is the time between call lights which is the SME estimate "Call Light Frequency." When the task is finished, one entity is set to itself to restart the delay and another is sent to "61 Random Call Light."
61 Random Call Light	-	This task is used to decide which staff member handles the call light. It can only start if the patient is in the MSU. The call light can be assigned to the charge nurse, the assigned nurse, or the assigned technician. The probabilities that it is assigned to any of the staff members is based on the SME estimates "Nurse Call Light Probability," "Technician Call Light Probability," and "Charge Nurse Call Light Probability."
34 Handle Call Light	Charge Nurse	This task represents the charge nurse handing a call light and only starts if the charge nurse is assigned to handle the call light. The task starts immediately because a call light is an urgent task. The VACP value=20.8 and the duration of the task uses the SME estimate "Call Light Durations."
104 Nurse Handles Call Light	-	This task simply changes PatientInfo[Entity.Tag,0] to 1 so that the assigned nurse handles the call light.
103 Tech Handles	-	This task simply changes PatientInfo[Entity.Tag,0] to 2

Call Light		so that the assigned technician handles the call light.
125_# Shift Changes	All	All of the staff shift changes tasks represent their shift change. They all start when the staff member is first free after 06:00 and 18:00. The durations of the task depends on the type of staff member. Charge nurse duration uses the SME estimate "CN Change Shift Duration," shift leader duration uses "Shift Leader Change Shift Duration," nurse durations use "Nurse Change Shift Duration," and technician durations use "Tech Change Shift Duration." The VACP value=12.3 for all staff members.
70-75_3 Receive Report	Nurse#	This task represents the task of receiving the report of the new patient from the patient's previous unit. This task starts immediately because it needs to be done quickly before the patient arrives. When the task is finished, PatientInfo[Entity.Tag,2] is changed to 1 to allow the patient to arrive in the MSU. The VACP value=16.5 and the duration uses the SME estimate "Receive Report Duration."
70-75_4 Preview Orders/Patient Info	Nurse#	This task represents the nurse looking at the new patient's record after they have received the report. It start immediately so that it is done before the patient arrives. The VACP value=11.9 and the duration uses the SME estimate "Preview Patient Info Duration."
70-75_2 Room Prep	Nurse#	This task represents the nurse preparing the room for the new patient. It is done immediately so that the room is ready as soon as possible. The VACP value=9.2 and the duration uses the SME estimate "Room Prep Duration."
70-75_8 Patient Arrive	-	This task represents the patient arriving which occurs after the assigned nurse takes the report of the patient (PatientInfo[Entity.Tag,1]==1). This task sends an entity to "Complete Admission Notes," "Med Delay," "2 hr Delay," "Handle Call Light," "12 hr Delay," and "Labs."
70-75_13 Complete Admission Notes	Nurse#	This task represents the nurse filling out the admission notes and performing any necessary actions for them. It can only start when the nurse is not busy (Nurse#==0) and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=22.6 and the duration uses the SME estimate "Admission Notes Duration."

70-75_14 Perform Admission Orders	Nurse#	This task represents the nurse performing any admission orders that a doctor makes for the new patient. It is done after the admission notes are finished. It can only start when the nurse is not busy (Nurse#==0) and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=23.6 and the duration uses the SME estimate "Perform Admission Orders Duration."
70-75_9 Med Delay	-	This task is used to decide when a patient needs medication. The duration of the task is either 43200 seconds if PatientInfo[Entity.Tag,3]==0 or 21600 if PatientInfo[Entity.Tag,3]==1. When the task is completed, it restarts by sending an entity to itself and it also sends an entity to "Administer Meds."
70-75_ 7 Administer Meds	Nurse#	This task represents the nurse getting medication and giving it to a patient. It can only start when the nurse is not busy (Nurse#==0) and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=22.6 and the duration uses the SME estimate "Administering Meds Duration."
70-75_25 2 hr delay	-	This task is used to space out Q2h Rounding by 2 hours so the task duration is exactly 2 hours. The task only starts if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1). When the task is completed, it restarts by sending an entity to itself and it also sends an entity to "Q2h Rounding."
70-75_22 Q2h Rounding	Nurse#	This task represents the nurse checking on the patient every 2 hours. It can only start when the nurse is not busy (Nurse#==0) and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=16.8 and the duration uses the SME estimate "Q2h Rounding Duration."
70-75_24 Handle Call Light	Nurse#	This task represents the nurse handing a call light and only starts if the nurse is assigned to handle the call light (PatientInfo[Entity.Tag,0]==1). The task starts immediately because a call light is an urgent task. The VACP value=20.8 and the duration of the task uses the SME estimate "Call Light Durations."
70-75_34 12 hr Delay	-	This task is used to space out Full Assessments by 12 hours so the task duration is exactly 12 hours. When the task is completed, it restarts by sending an entity to itself and it also sends an entity to "Full Assessment."

70-75_30 Full Assessment	Nurse#	This task represents the nurse fully assessing a patient which is done once per shift. It can only start when the nurse is not busy (Nurse#==0) and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=22.6 and the duration uses the SME estimate "Full Assessment Duration."
70-75_35 Labs	-	These functions contain the task networks for nurses collecting labs. They are identical to the lab function used in the technician and shift leader functions except for the "Nurse Collect#" and "Tech Collect#" tasks.
70-75_29 D/C Orders Received	-	This task is used to initiate discharge tasks. It only starts when PatientInfo[Entity.Tag,1] equals 2. It sends an entity to "Perform Discharge Orders."
70-75_19 Perform Discharge Orders	Nurse#	This task represents the nurse performing discharge orders for a patient. It starts if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) regardless of how busy the assigned nurse is because it is an urgent task. The VACP value=23.6 and the duration uses the SME estimate "Perform Discharge Orders Duration."
70-75_17 Prepare Discharge Papers	Nurse#	This task represents the nurse preparing paperwork for a patient to discharge. It starts immediately after discharge orders because it is an urgent task. The VACP value=16.2 and the duration uses the SME estimate "Prepare/Print Discharge Papers Duration."
70-75_18 Prepare PT for D/C	Nurse#	This task represents the nurse preparing a patient for discharge. It start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) regardless of how busy the assigned nurse is because it is an urgent task. The VACP value=14.3 and the duration uses the SME estimate "Prepare PT for Discharge Duration." When the task is finished, it either sends an entity to "Nurse D/C Patient" or "Tech D/C Patient." The probabilities it uses to determine who discharges the patient are the SME estimate "Nurse Discharge PT Probability" and "Technician Discharge PT Probability."
70-75_20 Nurse D/C Patient	Nurse#	This task represents the nurse discharging the patient from the unit. The task starts immediately because it is an urgent task. When the task is completed, PatientInfo[Entity.Tag,1] is set to 3 to show that the patient is discharged. The VACP value for the task is 12.2 and the task duration uses the SME estimate "Discharge from Unit Duration."

70-75_33 Tech D/C Patient	-	This is a filler task used to simulate the technician discharging the patient from the unit. This task has no assigned operator because the task which really represents a technician discharging a patient is located in the technician functions. Instead, this task is only used to change the PatientInfo[Entity.Tag,1] to 3 to show that the patient is discharged. Since there is no assigned operator, there is no VACP value. The task starts immediately because it is an urgent task and the task duration uses the SME estimate "Discharge from Unit Duration."
70-75_10 Patient Discharged	-	This task is used to initial post discharge tasks and send an entity to the "999 END" task once the patient is discharged (PatientInfo[Entity.Tag,1]==3) which is a release condition.
70-75_5 Strip Room	Nurse#	This task represents the nurse striping the room after a patient is discharged. It starts immediately so that the room is ready for a new patient as soon as possible. The VACP value=8.8 and the task duration uses the SME estimate "Strip Room Duration."
70-75_6 Close/Turn In Records	Nurse#	This task represents the nurse finish any paperwork for a patient after they are discharged and the room has been stripped. The task only starts when the nurse is not busy (Nurse#Busy==0) because it is not urgent. The VACP value=16.2 and the task duration uses the SME estimate "Close/Turn-in Records Duration."
70-75_999 END		When the "Patient Discharged" task releases the entity to this task, the NursePatientLoad for the assigned nurse is reduced by 1 to update the current patient load of the nurse. Also Nurse#AveragePatientLoad is updated (Nurse#AveragePatientload = Nurse#AveragePatientload+(Clock-Nurse#Clock)*NursePatientLoad[#,0]) and Nurse#Clock=Clock as part of the Nurse#AveragePatientLoad snapshot.
77-80 Technician# and 9 Shift Leader	-	The functions include the task network for each of the 4 technicians and the shift leader. The only difference between the functions are the operators. Each function is specifically used for its corresponding technician and shift leader.
77-80_1 Room Prep	Tech#, Shift Leader	This task represents the technician or shift leader preparing the room for the new patient. It is done immediately so that the room is ready as soon as possible. The VACP value=9.2 and the duration uses the SME

		estimate "Room Prep Duration."
77-80_11 Patient Arrive	-	This task represents the patient arriving which occurs after the assigned nurse takes the report of the patient (PatientInfo[Entity.Tag,1]==1). This task sends an entity to "4 hr Delay," "Handle Call Light," "Tests," and "Labs."
77-80_7 Handle Call Light	Tech#, Shift Leader	This task represents the technician or shift leader handing a call light and only starts if the technician or shift leader is assigned to handle the call light (PatientInfo[Entity.Tag,0]==2). The task starts immediately because a call light is an urgent task. The VACP value=20.8 and the duration of the task uses the SME estimate "Call Light Durations."
77-80_53 Tests	-	These functions contain the task networks for the technicians and shift leaders transporting patients to tests. The technician and shift leader test functions are identical to each other.
77-80_54 Labs	-	These functions contain the task networks for the technicians and shift leaders collecting labs. The technician and shift leader lab collection function are identical to each other. They are also identical to the lab function used in the nurse functions except for the "Nurse Collect#" and "Tech Collect#" tasks.
77-80_14 4 hr Delay	-	This task is used to space out Vitals, I/O, Neuro tasks by 4 hours so the task duration is exactly 4 hours. When the task is completed, it restarts by sending an entity to itself and it also sends an entity to "Vitals, I/O, Neuro."
77-80_9 Vitals, I/O, Neuro	Tech#, Shift Leader	This task represents the technician or shift leader checking the vital signs, ins and outs, and neurological condition of patient. It start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) regardless of how busy the assigned technician or shift leader is because it is an urgent task. The VACP value=19.2 and the duration uses the SME estimate "Vitals, I/Os, Neuro Duration."
77-80_8 2 hr Delay	-	This task is used to delay the Q2h rounding by 2 hours after the Vitals, I/O, Neuro task so the task duration is exactly 2 hours but it only starts if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1). When the task is completed, it sends an entity to "Q2h Rounding."

77-80_2 Q2h Rounding	Tech#, Shift Leader	This task represents the technician or shift leader checking on the patient every 2 hours. Since the nurse also checks on the patient during "Vitals, I/O, Neuro", the task network only has this task 2 hours after "Vitals, I/O, Neuro" which is done every 4 hours. It can only start when the technician or shift leader is not busy and the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2). The VACP value=16.8 and the duration uses the SME estimate "Q2h Rounding Duration."
77-80_12 D/C Orders Received	-	This task is used to initiate discharge tasks. It only starts when PatientInfo[Entity.Tag,1] equals 2. It sends an entity to "Remove Invasive Devices."
77-80_5 Remove Invasive Devices	Tech#, Shift Leader	This task represents the technician or shift leader removing invasive devices before they are discharged. It start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) regardless of how busy the assigned technician or shift leader is because it is an urgent task. The VACP value=7.2 and the duration uses the SME estimate "Remove Invasive Devices Duration." When the task is finished, it either sends an entity to "Nurse D/C Patient" or "Tech D/C Patient." The probabilities it uses to determine who discharges the patient are the SME estimate "Nurse Discharge PT Probability" and "Technician Discharge PT Probability."
77-80_16 Tech D/C Patient	Tech#, Shift Leader	This task represents the tech discharging the patient from the unit. The task starts immediately because it is an urgent task. The VACP value for the task is 12.2 and the task duration uses the SME estimate "Discharge from Unit Duration."
77-80_55 Nurse D/C Patient	-	This is a filler task used to so that probabilities can be assigned in the "Remove Invasive Devices" task. The task has no other purpose so there is no operator, VACP value, or task duration.
77-80_13 Patient Discharged	-	This task is used to initial post discharge tasks and send an entity to the "999 END" task once the patient is discharged (PatientInfo[Entity.Tag,1]==3) which is a release condition.
77-80_6 Strip Room	Tech#, Shift Leader	This task represents the technician or shift leader striping the room after a patient is discharged. It starts immediately so that the room is ready for a new patient as soon as possible. The VACP value=8.8 and the task duration uses the SME estimate "Strip Room Duration."

77-80_999 END	-	When the "Patient Discharged" task releases the entity to this task, the TechPatientLoad for the assigned technician or shift leader is reduced by 1 to update the current patient load. Also Tech# or ShiftLdrAveragePatientLoad is update (Tech# or ShiftLdrAveragePatientload = Tech# or ShiftLdrAveragePatientload+(Clock-Tech# or ShiftLdrClock)*TechPatientLoad[#,0]) and Tech# or ShiftLdrClock=Clock as part of the Tech# or ShiftLdrAveragePatientLoad snapshot.
77-80_54_19 Split Path	-	This task is used to simply split the entities path in two so that one entity goes to "24 Hour Delay" and the other goes to "Lab Today?."
77-80_54_18 24 Hour Delay	-	This task is simply a timer which has a duration of exactly 24 hours. It sends an entity back to "Split Path" for the lab task network to restart each day.
77-80_54_1 Lab Today?	-	This task decides how many labs a patient will need to have drawn in a day. The task can only start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1). It uses the SME estimates "No Lab Percentage," "One Lab Percentage," "Two Lab Percentage," and "Three Lab Percentage" to decide which path to send the entity.
77-80_54_3 No More Labs	-	This task is reached when there are no more labs. It sends the entities to "999 End."
77-80_54_# One, Two, or Three Labs	-	These tasks use random delays to space out the labs so that they occur at different times in the day. They also use the SME estimates "Nurse Lab Collection Probability" and "Technician Lab Collection Probability" to decide which staff member will draw the lab.
77-80_54_# Tech Collect#	Tech#, Shift Leader	This task represents a technician or shift leader drawing and transport a lab for patient. It only occurs if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) and if the staff member is not busy (Tech1Busy==0 or ShiftLdrBusy==0). The VACP value=14.6 and the duration of the task uses the SME estimate "Duration of Lab Collection and Transport."
77-80_54_# Nurse Collect#	-	In the "Technician#" and "Shift Leader" functions, the "Nurse Collect#" task is used a filler to avoid redundancy since the nurse actually performs this task in the "Nurse#" functions. For this reason, there is no operator assigned to this task and no VACP value. However, the task still has a duration which uses the SME estimate "Duration of Lab Collection and Transport" and it can only start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2).

77-80_54_# Delay#	-	These tasks use random delays to space out the labs so that they occur at different times in the day. They also use the SME estimates "Nurse Lab Collection Probability" and "Technician Lab Collection Probability" to decide which staff member will draw the lab.
70-75_35_7 Split Path	-	This task is used to simply split the entities path in two so that one entity goes to "24 Hour Delay" and the other goes to "Lab Today?."
70-75_35_6 24 Hour Delay	-	This task is simply a timer which has a duration of exactly 24 hours. It sends an entity back to "Split Path" for the lab task network to restart each day.
70-75_35_2 Lab Today?	-	This task decides how many labs a patient will need to have drawn in a day. The task can only start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1). It uses the SME estimates "No Lab Percentage," "One Lab Percentage," "Two Lab Percentage," and "Three Lab Percentage" to decide which path to send the entity.
70-75_35_14 No More Labs	-	This task is reached when there are no more labs. It sends the entities to "999 End."
70-75_35_# One, Two, or Three Labs	-	These tasks use random delays to space out the labs so that they occur at different times in the day. They also use the SME estimates "Nurse Lab Collection Probability" and "Technician Lab Collection Probability" to decide which staff member will draw the lab.
70-75_35_# Tech Collect#	-	In the "Nurse#" functions, the "Tech Collect#" task is used a filler to avoid redundancy since the technician actually performs this task in the "Technician" and "Shift Leader" functions. For this reason, there is no operator assigned to this task and no VACP value. However, the task still has a duration which uses the SME estimate "Duration of Lab Collection and Transport" and it can only start if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2).
70-75_35_# Nurse Collect#	Nurse#	This task represents a nurse drawing and transport a lab for a patient. It only occurs if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1 or 2) and if the staff member is not busy (Nurse1Busy==0). The VACP value=14.6 and the duration of the task uses the SME estimate "Duration of Lab Collection and Transport."
70-75_35_# Delay#	-	These tasks use random delays to space out the labs so that they occur at different times in the day. They also use the SME estimates "Nurse Lab Collection

		Probability" and "Technician Lab Collection Probability" to decide which staff member will draw the lab.
77-80_53_4 Test Today?	-	This task only releases tests when it is the dayshift (Shift%2!=0) because tests are done during the day. When it is the day shift, it uses the SME estimates "No Test Percentage," "One Test Percentage," "Two Test Percentage," and "Three or More Test Percentage" to decide how many tests the patient has that day.
77-80_53_# One,Two, or Three Test	-	These tasks are random delays to space out the tests so that they do not all occur at once.
77-80_53_# Transport to Test#	Tech#, Shift Leader	All of the "Transport to Test" tasks are identical. They represent the technician or shift leader taking the patient to the test which is in a different part of the hospital. They occur immediately if the patient is in the MSU (PatientInfo[Entity.Tag,1]==1) because they need to be done at scheduled times. This tasks make PatientInfo[Entity.Tag,1] equal to 4 to indicate that the patient is at a test. The VACP value=10.2 and the task duration uses the SME estimate "Duration of Test Transport."
77-80_53_# Retrieve from Test#	Tech#, Shift Leader	All of the "Test Duration" tasks are identical. They represent the technician or shift leader retrieving the patient from the test which is in a different part of the hospital. The duration of the task uses the SME estimate "Test Duration." They occur immediately if the patient is still at the test (PatientInfo[Entity.Tag,1]==4). It checks to see if PatientInfo[Entity.Tag,1] still equals 4 because if the value has changed, it means that discharge orders were received while they were at the test which could cause coding errors. When the task is completed, PatientInfo[Entity.Tag,1] is changed back to 1 to indicate that they are back in the MSU. The VACP value=10.2 and the task duration uses the SME estimate "Duration of Test Transport."
77-80_53_# Test Duration#	-	All of the "Retrieve from Test" tasks are identical. They represent the time that the patient is at the test.
77-80_53_# Test Delay#	-	These tasks are random delays to space out the tests so that they do not all occur at once.

77-80_53_5 No More Tests	-	This task is reached when there are no more tests for a given patient. The task holds the entities and releases them to "Test Today?" once night has started and if the patient has not been discharged (Shift%2==0 && PatientInfo[Entity.Tag,1]==1).

Table 33: IMPRINT Variables

Variable Name	Description
Admit	Integer variable used in the DailyAdmits Snapshot which keeps track of the number of admits each day. Starts as zero.
BedUtilization	Integer variable used to track number of patients in the MSU at a given moment. Maximum is 39 beds. Starts as zero. Also used in the BedUtilization snapshot.
Clock	FloatingPoint variable used to track time. Starts at zero.
CNBusy	Integer variable used to indicate if the charge nurse is busy or free. Some tasks are only performed when the charge nurse is not busy. Starts as zero. When CNBusy equals zero, the charge nurse is free. Otherwise, the charge nurse is busy.
DayOfWeek	Integer variable used to track the day of the week. 0=Sunday, 1=Monday….6=Saturday
DayoorNight	Integer variable used to track the day and night. 0=night, 1=day
Nurse#AveragePatientload	FloatingPoint variable used in the Nurse#AveragePatientLoad snapshot to find the time weighted average patient load for nurse# in the final week of the simulation.
Nurse#Busy	Integer variable used to indicate if the nurse# is busy or free. Some tasks are only performed when the nurse# is not busy. Starts as zero. When Nurse#Busy equals zero, the nurse# is free. Otherwise, the nurse# is busy.
Nurse#Clock	Floating point variable used in conjunction with Nurse#AveragePatientload variable in the Nurse#AveragePatientLoad snapshot.
NursePatientLoad	Floating point, 7 by 1, array variable used to keep track of the number of patients assigned to each nurse at a given moment. Row zero is for nurse1, row one is for nurse2 and so on. Each cell in the array is initially zero. The variable is used in the patient assignment logic.

PatientInfo	Integer, 1000 by 4, array variable used to track specific information for each specific patient. All cells are initially zero. Each row is a new patient. Column 0 is used to assign the call light staff member: 1=nurse, 2=shift leader. Column 1 is used to track the patient's location: 0=Pre-admit, 1=admitted, 2=discharge orders received, 3=discharged, 4=at test. Column 2 is used to track if the assigned nurse has received report: 0=not received, 1=received. Column 3 is used to track medication schedule: 0=12hrs, 1=6hrs.
PatientLoadMultiplier	Floating point variable used in the alternate models to change the patient load. Initially set to 1.
Shift	Integer variable used to track the day and night shift. Initially set to 2. Even numbers=night shift and odd numbers=day shift.
ShiftLdrAveragePatientload	FloatingPoint variable used in the ShiftLdr#AveragePatientLoad snapshot to find the time weighted average patient load for the shift leader in the final week of the simulation.
ShiftLdrBusy	Integer variable used to indicate if the shift leader is busy or free. Some tasks are only performed when the shift leader is not busy. Starts as zero. When ShiftLdrBusy equals zero, the shift leader is free. Otherwise, the shift leader is busy.
ShiftLdrClock	Floating point variable used in conjunction with ShiftLdrAveragePatientload variable in the ShiftLdrAveragePatientLoad snapshot.
Tech#AveragePatientload	FloatingPoint variable used in the Tech#AveragePatientLoad snapshot to find the time weighted average patient load for the tech# in the final week of the simulation.
Tech#Busy	Integer variable used to indicate if the tech# is busy or free. Some tasks are only performed when the tech# is not busy. Starts as zero. When Tech#Busy equals zero, the tech# is free. Otherwise, the tech# is busy.
Tech#Clock	Floating point variable used in conjunction with Tech#AveragePatientload variable in the Tech#AveragePatientLoad snapshot.
TechPatientLoad	Floating point 6 by 1 array variable used to keep track of the number of patients assigned to each tech at a given moment. Row zero is for tech1, row one is for tech2 and so on. Each cell in the array is initially zero. The variable is used in the patient assignment logic.
WeeklyDischarge	Integer variable used in the WeeklyDischarge snapshot to track the number of patients which are discharged during the third week of the simulation. Initially set to zero.

Table 34: Snapshots

Snapshots	Description
BedUtilization	Snapshot which tracks the number of patients in the MSU at midnight for each day during the third week of a run. Uses the BedUtilization variable.
DailyAdmits	Snapshot which uses the Admit and DayOfWeek variables to track the number of patients which are admitted each day of the week during the third week of a model run.
Nurse#AveragePatientLoad	Snapshot which tracks the time weighted average patient load for nurse#. Outputs a number for each of the 3 weeks during a model run. Uses Nurse#AveragePatientload variable.
ShiftLdrAveragePatientLoad	Snapshot which tracks the time weighted average patient load for the shift leader. Outputs a number for each of the 3 weeks during a model run. Uses ShiftLdrAveragePatientload variable.
Tech#AveragePatientLoad	Snapshot which tracks the time weighted average patient load for tech#. Outputs a number for each of the 3 weeks during a model run. Uses Tech#AveragePatientload variable.
TurnedAwayPatients	Snapshot which tracks the time that any patient is turned away during a run. The time outputs can be used to see the number of turned away patients and when they occur.
WeeklyDischarge	Snapshot which tracks the number of patients which are discharged during the third week of a run.

Task Network Figures

The figures below show the different parts of the task network used in the MSU IMPRINT model. Rounded boxes are tasks and square boxes are functions. Functions contain sub task networks. Each task and function is described in the Model Task Logic table above. Purple boxes have no operator and are used for system logic. Yellow boxes are performed by the charge nurse. Orange boxes are performed by the shift leader. Blue boxes are performed by a nurse. Green boxes are performed by a technician.

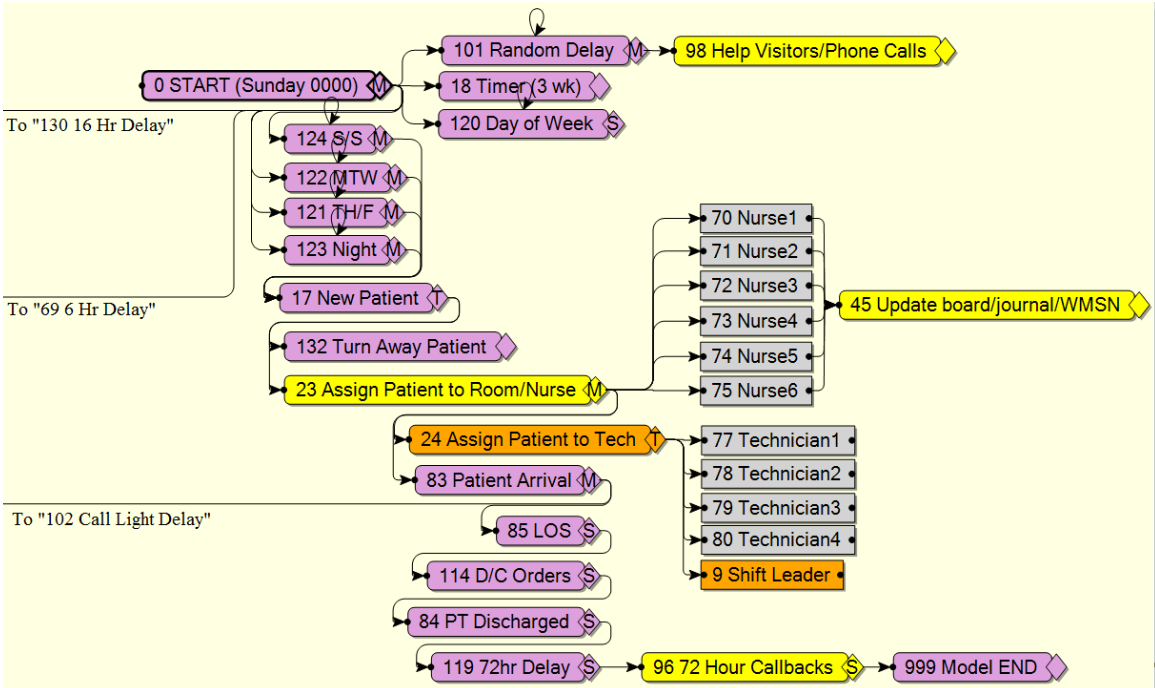

Figure 13: Root Task Network

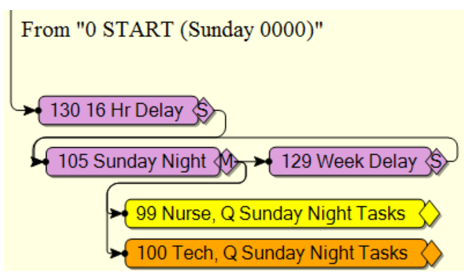

Figure 14: Root Task Network (Sunday Night Tasks)

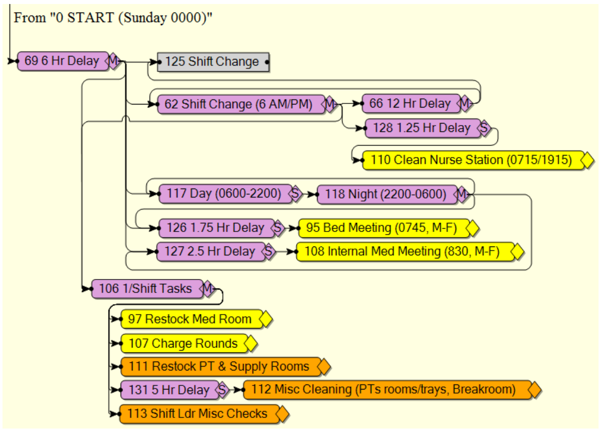

Figure 15: Root Task Network (Shift Tasks)

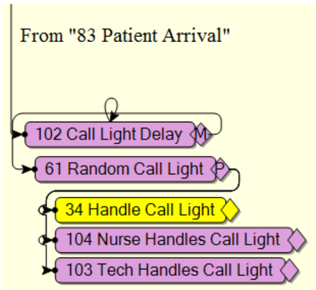

Figure 16: Root Task Network (Call Light Tasks)

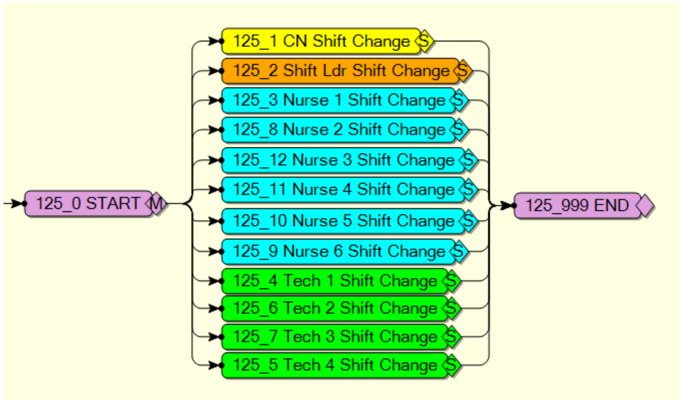

Figure 17: Shift Change Function

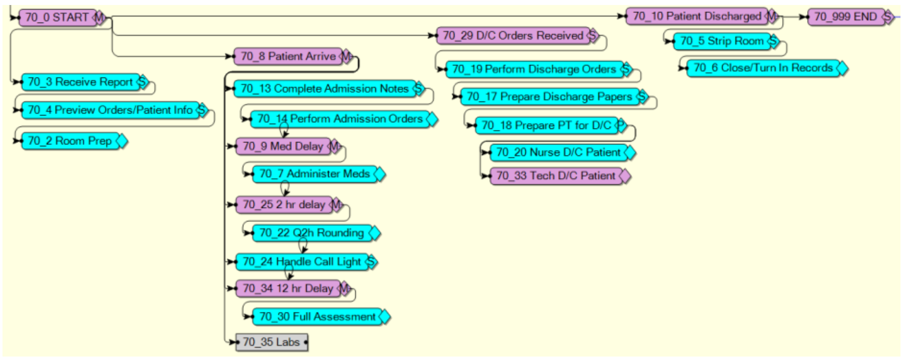

Figure 18: Nurse Functions

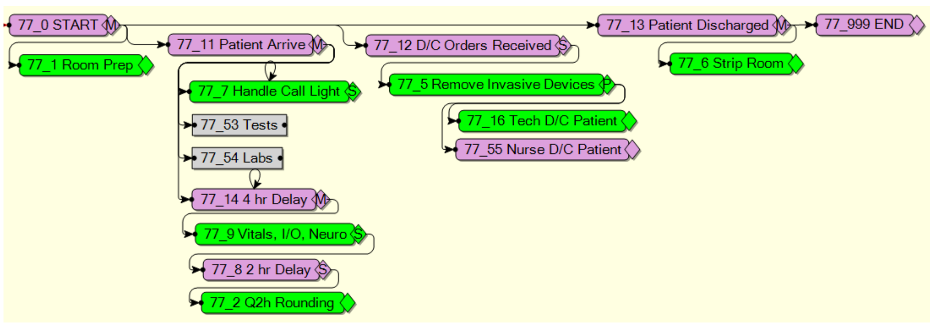

Figure 19: Technician, and Shift Leader, Functions

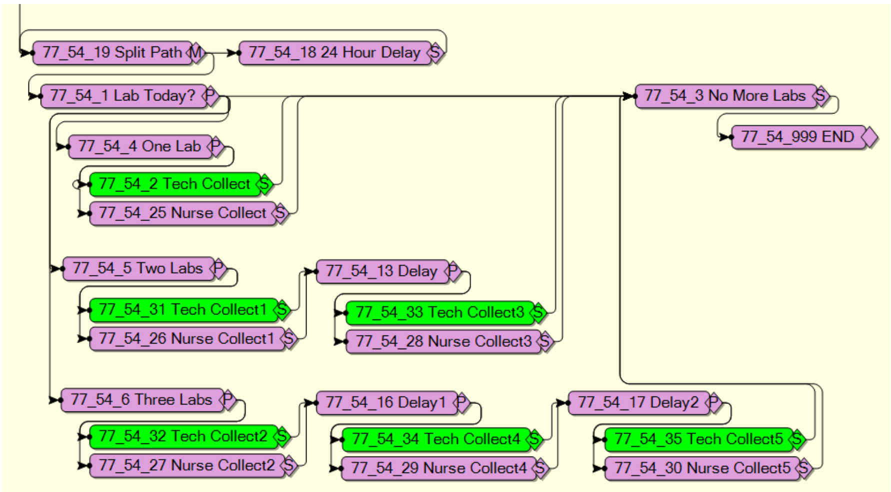

Figure 20: Technician Lab Function

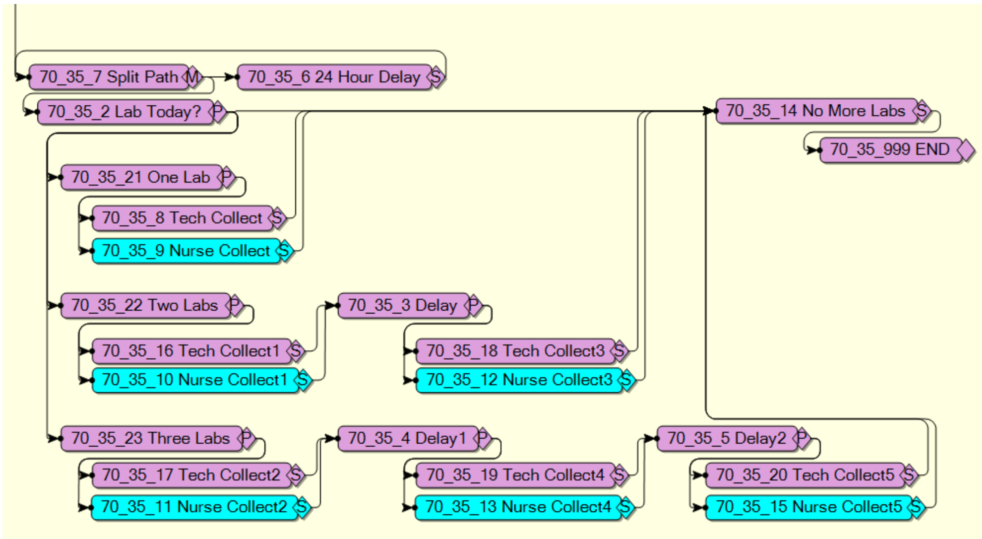

Figure 21: Nurse Lab Function

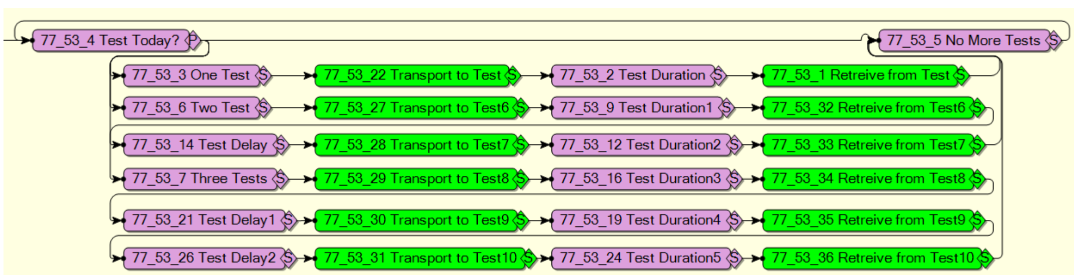

Figure 22: Test Function

Model Replications

The number of replications used to generate IMPRINT outputs were determined using equation 1 below where n=replications needed, n0=initial number of replications, ho=initial half-width, and h=desired half-width. The half-width of the weekly discharge metric was used to determine the number of replications because patient demand has a large impact on the workload outputs of staff members. As Table 35 shows, an initial set of 10 IMPRINT runs were used to create an initial weekly discharge half-width. Equation x determined that 58.56 runs were required to reach the desired half-width. The researched decided to round up and use 60 replications for all baseline and alternate model outputs.

$$\boldsymbol{n \cong n_0 \frac{h_0^2}{h^2}} \tag{1}$$

Table 35: Model Replications

MSU Records Weekly Discharge Half-Width (h)	2.18
Initial Number of Replications (n0)	10.00
Initial Weekly Discharge Half-Width (h0)	5.28
Number of Replications needed (n)	58.56

Appendix E – Assumptions and Justifications

Every model requires some number of assumptions to be made. Table 36 below lists the assumptions for the baseline model and the justifications for each assumption.

Table 36: Baseline Model Assumptions

Baseline Model Assumptions	Justification
SME estimates are accurate approximations to real-world data.	SMEs have cared for thousands of patients which help them to make accurate estimates.
Data collected and observations are representative of normal conditions.	The researchers work to reduce the Hawthorne effect by informing the staff that their information will remain confidential and ask them to work like they normally would.
Patients can have an unlimited number of tasks performed on them at the same time while some tasks may interfere in reality.	This assumption is justified because unrealistic instances are expected to be rare. Also, location restrictions are placed on most tasks. Allowing unlimited tasks to be performed makes the model simpler and less restrictive to better allow for multitasking.
Medical staff cannot start most tasks on patients when they are out of the MSU for testing.	Making employees wait until a patient returns to perform a tasks which require the presence of the patient is mostly realistic. In reality, some tasks may be started, like gather supplies, before the patient returns to make the task faster once the patient does return. This assumption is justified because it is a simple way to make the model more realistic despite having some unrealistic aspects.
Unless specified, employees can multitask any number of tasks	In reality, tasks would be dropped or postponed when a worker reaches a workload limit. However, the model allows unlimited multitasking to show the demands being places on the worker.
Employees can simultaneously perform tasks which, in reality, would require them to be in multiple locations at the same time.	This assumption is justified because the goal of the model is to show the workload demands on the employees at a given time. Adding the full logic of what can and cannot be multitasked would be infeasible for this research.
The model does not account for the two different MSU floors	In reality, the two floors adds complexity to the patient assignment process. Distinguishing between floors would add more detail to the model than is necessary for the purposed of this research and it would make the model much more complicated.

Staffing numbers are constant over time	The staffing numbers of the MSU were determined from a real-world schedule which indicate that the MSU uses a mostly flat rate manning policy. Roughly the same number of staff members are working during each day of the week and time of the day. In reality, the levels are could change temporarily due to significant increases in patient load; however, this rarely happens and cannot be sustained for long periods of time. Attempting to vary staffing levels in response to patient loads would not be feasible with the current design of the IMPRINT model. It would also reduce the effects of patient load on mental workload.
Patients are only discharged	In reality, patients could be transferred to other units in the hospital. However, the Essentris data discharged 91.1% of patients from the MSU. The other 8.9% who transfer out and back into MSU are accounted for by merging their separate stays into one.
Patients can only be admitted after their assigned nurse receives their report call	In reality, there are a small number of instances where a non-assigned nurse for a patient receives the report for another nurse. However, the logic used in the model is what actually happens the vast majority of the time. Accounting for the other rare instances would have little impact on results.
Medication demands of a patient are determined when they enter the model and do not change	In reality, the medication demands of a patient may change over their stay. However, most patients stay the same so it is difficult to determine why the demands would change and it would likely have little effect on the workload results.
All employees perform each given tasks at same rate	In reality, employees perform tasks differently based on preference and experience. These differences are not explicitly accounted for in the model; but, it is captured to an extent in the model variability. Accounting for differences in employee experience is not part of this research.
All tasks are 100% successful	Instead of explicitly modeling errors, unsuccessful tasks are accounted for in task duration variability. In other words, the mode represents when tasks are performed correctly, and the maximum durations represent extreme cases when things go wrong. Modeling in this way requires fewer metrics and less model logic; however, it provides less information and could be less realistic.

Patients are grouped into a single population	Patients are not distinguished based on their previous unit, diagnosis, or any other attribute. They are treated as a single population because distinguishing between different types of patient would introduce error into the model because of the limited set of data which it is built upon. It is also not required for the purposes of this research.
The model does not include dynamic workload balancing logic. For example employees do not share tasks when one of them is busy and the other is idle.	In reality, staff help each other and share tasks when one employee is overloaded. The model does not account for this for simplicity and to better allow for overworking and to keep the model simple. The model represents the MSU if the staff only ever performed the tasks that they are responsible for.
Patient Length of Stay is predetermined and not based on patient recovery	In reality, a patient's length of stay is usually determined by their medical condition. Since the model does not model a patient's medical condition, the length of stay is determined randomly using a distribution built from real world length of stay times.
Discharges occur at any time of the day	In reality, discharges can happen at any time; but, most occur during the day shift. The model determines when to discharge a patient based on their length of stay which is predetermined so there is not a simple way to restrict discharges to the day shift without causing problems to the length of stay metric.
MSU is isolated from the effects of other units	The model does not account for any logic relating to other units. For example, some logic involving labs, tests, patient arrivals, or discharges could be influenced by other units. This assumption is relevant for the alternate models. Increased patient loads could influence other units which has secondary effects on the MSU. None of these potential effects are considered because they are unpredictable.

Appendix F – Baseline Model Validation

To ensure that the IMPRINT model was an accurate representation of the real-world MSU, the researchers validated workload and throughput metrics. To validate workload, the complexity of tasks were compared to SME rank orders of tasks. Workload was also validated by comparing model outputs of idle time to SME estimates. Throughput was validated by comparing model outputs of bed utilization and weekly discharge to SME estimates. The results of validated for each metric are provided below.

Workload Validation

The workload demands of tasks were validated by asking SMEs to rank order the demands of the main IMPRINT tasks for nurses and technicians. The charge nurse and shift leader specific tasks are not included. Two nurse subjects and two technician subjects were asked to rank order the tasks in order of most mentally demanding (1) to least mentally demanding (10) as shown in Tables 37 and 38. The ranks provided by each subject were averaged. The averaged rank numbers were used by the researchers to categorize each task into one of three workload categories: High, Medium, and Low. The VACP values for the tasks in IMPRINT were compared to the workload categories and increased or decreases until the VACP values matched the SME estimates.

Table 37: Nurse Task Workload Demands

Nurse Main Tasks	Subject 11	Subject 9	Average	Workload Category	IMPRINT VACP
Performing Admission Orders	1	1	1	High	23.6
Administering Medication	3	2	2.5	High	22.6
Full Assessment	5	3	4	High	22.6
Handling Call Light	2	7	4.5	Medium	20.8
Q2h Rounding	4	6	5	Medium	16.8
Receiving Report	7	4	5.5	Medium	16.5
Collecting Labs	6	5	5.5	Medium	14.6
Preparing Room	9	8	8.5	Low	9.2
Stripping Room	8	9	8.5	Low	8.8

Table 38: Technician Task Workload Demands

Technician Main Tasks	Subject 10	Subject 8	Average	Workload Category	IMPRINT VACP
Handling Call Light	1	1	1	High	20.8
Vitals, I/O, Neuro	4	3	3.5	High	19.2
Q2h Rounding	2	6	4	Medium	16.8
Collecting Labs	3	7	5	Medium	14.6
Transporting PT to Test	6	4	5	Medium	10.2
Preparing Room	8	2	5	Medium	9.2
Stripping Room	7	5	6	Low	8.8
Removing Invasive Devices	5	8	6.5	Low	7.2

Workload was also validated by validating nurse and technician idle time. Two nurses and two technicians were asked to provide a 95% confidence interval of the average percentage of time in a week that they experience idle time (zero or very light workload). Idle time is highly dependent on patient load so each employee provided percentages for two common patient loads. The estimates from the two SMEs were averaged as shown in Tables 39-40. The idle time and average patient load outputs for ten IMPRINT replications were used for idle time validation and included in Table 41and Table 42. The idle time 95% confidence intervals of the IMPRINT outputs are shown in Table 41. The average patient load from the IMPRINT models were averaged and used to interpolate/extrapolate the SME confidence intervals which are compared to the model

confidence intervals in Table 43. The SME and model 95% confidence intervals overlap so idle time is successfully validated.

Despite a successful validation, there are some differences between the confidence intervals. The SME intervals are much larger than the IMPRINT intervals. Also, the IMPRINT intervals are centered to the right of the SME intervals. The differences are either due to poor SME estimates or how the IMPRINT model handles multitasking. For example, during slow times in the MSU, employees are less likely to multitask as much as the IMPRINT models predict. The implications of this difference could include overestimates of idle time for runs with low patient demands. However, it is expected that the idle time results of runs with high patient demands will be the most accurate representations of the real-world.

Table 39: Nurse Idle Time Estimates

Nurse Percent of Time at Zero Workload	Subject 11	Subject 9	Average
3 Patient Workload Estimate	35%	40%	38%
3 Patient Workload 95% Confidence Interval	25% - 45%	25% - 55%	25% - 50%
4 Patient Workload Estimate	25%	30%	28%
4 Patient Workload 95% Confidence Interval	15% - 35%	20% - 40%	17.5% - 37.5%

Table 40: Technician Idle Time Estimates

Technician Percent of Time at Zero Workload	Subject 10	Subject 8	Average
4 Patient Workload Estimate	40%	50%	45%
4 Patient Workload 95% Confidence Interval	30% - 50%	40% - 60%	35% - 55%
6 Patient Workload Estimate	25%	30%	28%
6 Patient Workload 95% Confidence Interval	10% - 40%	20% - 40%	15% - 40%

Table 41: IMPRINT Idle Time Outputs (10 Runs)

RNS:	1	2	3	4	5	6	7	8	9	10	Mean	Std Dev	Number	95% CI	
Weekly Discharge	59	58	45	51	39	54	53	54	38	54					
Nurse1	26.1%	23.9%	49.5%	44.0%	50.0%	38.0%	38.4%	38.2%	48.9%	35.5%	44.5%	9.4%	60	42.1%	47.0%
Nurse2	29.1%	29.4%	50.4%	41.9%	48.5%	41.5%	41.5%	44.3%	49.5%	34.0%					
Nurse3	24.2%	34.6%	57.9%	45.4%	48.6%	46.7%	43.1%	39.5%	51.5%	40.2%					
Nurse4	30.8%	30.6%	50.1%	47.2%	51.2%	41.7%	43.2%	48.6%	51.5%	41.5%					
Nurse5	31.0%	38.2%	59.0%	51.7%	57.0%	45.7%	44.6%	46.0%	56.1%	47.4%					
Nurse6	38.0%	41.5%	62.3%	56.6%	64.2%	53.9%	52.0%	50.0%	60.7%	46.3%					
Technician1	40.7%	42.7%	53.8%	51.6%	55.2%	43.1%	48.8%	55.2%	51.2%	48.1%	51.8%	6.4%	40	49.8%	53.9%
Technician2	40.3%	44.5%	56.6%	52.8%	54.8%	51.5%	51.6%	49.7%	57.2%	47.8%					
Technician3	43.0%	45.3%	63.8%	46.8%	60.8%	54.0%	53.7%	52.5%	60.6%	51.3%					
Technician4	39.5%	46.7%	60.1%	58.1%	65.2%	56.7%	56.2%	50.9%	59.2%	51.9%					

Table 42: IMPRINT Average Patient Load

RNS:	1	2	3	4	5	6	7	8	9	10	Mean
Weekly Discharge	59	58	45	51	39	54	53	54	38	54	
Nurse1	4.57	4.53	2.86	2.91	2.86	3.57	3.18	4.30	2.75	3.59	3.11
Nurse2	4.72	4.41	2.80	3.37	3.15	2.90	3.25	3.07	2.75	4.31	
Nurse3	4.44	3.76	2.35	3.41	2.17	2.57	2.79	3.09	2.46	3.36	
Nurse4	4.12	3.86	2.63	3.03	3.11	4.45	3.40	2.68	2.43	2.74	
Nurse5	3.37	3.34	2.08	2.86	2.17	3.63	2.64	3.50	2.37	2.41	
Nurse6	2.97	3.14	2.15	2.25	1.93	2.31	2.67	2.84	1.99	3.37	
Technician1	4.95	4.56	3.58	3.96	3.82	5.75	4.33	4.17	3.88	3.83	3.98
Technician2	5.99	5.00	2.79	4.05	3.92	4.07	2.93	3.21	3.46	5.23	
Technician3	4.81	4.63	2.82	4.71	3.10	3.89	3.92	3.82	2.95	3.94	
Technician4	4.51	4.25	3.23	3.42	2.90	3.83	3.22	4.65	2.99	4.09	

Table 43: Idle Time 95% Confidence Intervals

	Mean Patients	SME 95% CI		IMPRINT 95% CI	
Nurses	3.11	24.2%	48.6%	42.1%	47.0%
Technicians	3.98	35.2%	55.2%	49.8%	53.9%

Bed Utilization Validation

Bed Utilization is the number of patients in the MSU at midnight each day. The IMPRINT bed utilization is validated using the month of Essentris Data because the times of patient arrivals and discharges are more accurate in the Essentris data than the 2 MSU records. Since Essentris Records (28 days of data) are being used for validation, the number of data points are 28 as shown in Table 44. The same number of IMPRINT data points. The IMPRINT data points are collected using the BedUtilization snapshot which capture the number of patients in the MSU at midnight during the 3rd week of the first 4 runs (RNS 1-4). As Table 45 shows, the Essentris Records and IMPRINT data have a P-value of 0.891 so there is no significant difference between the two.

Table 44: Bed Utilization Data

MSU Records	IMPRINT Data
23	17
24	26
19	32
17	30
14	25
14	25
15	23
21	18
26	24
32	26
24	27
24	23
20	22
20	17
19	12
22	16
27	18
22	13
19	16
14	20
13	16
19	18
19	14
26	18
23	20
22	22
17	19
21	14

Table 45: Bed Utilization Confidence Intervals

Bed Utilization	**MSU Records 95% CI**	18.836	22.307
	IMPRINT 95% CI	18.390	22.396
	P-Value	0.891	

Weekly Discharge Validation

Weekly discharge is the number of patients which are discharged from the MSU in one week. It is used to validate the model throughput. Weekly discharge is validated using the 2 years of MSU records. In the IMPRINT model, weekly discharge is found by counting the number of patients that are discharged from the MSU during one full week (0000 Sunday to 2400 Saturday). The IMPRINT weekly discharge is acquired using the WeeklyDischarge snapshot which keeps track of the number of patients discharged during the 3rd week of each run. Since there are 2 years of MSU data (104 weeks), there are 104 data points. The same number of IMPRINT data points were collected by running the model 104 times (using random number seeds 1-104). Table 46 shows the MSU records and IMPRINT outputs. As Table 47 shows, the 95% confidence intervals of the MSU records and IMPRINT outputs overlap and have a P-value of 0.928, so there is no significant difference.

Table 46: MSU and IMPRINT Weekly Discharge Data

Week	MSU Records	IMPRINT Data	Week	MSU Records	IMPRINT Data	Week	MSU Records	IMPRINT Data
10/1/2013	42	59	6/3/2014	54	55	2/3/2015	62	52
10/8/2013	60	58	6/10/2014	61	67	2/10/2015	46	52
10/15/2013	49	45	6/17/2014	59	50	2/17/2015	53	56
10/22/2013	53	51	6/24/2014	48	62	2/24/2015	65	62
10/29/2013	55	39	7/1/2014	30	43	3/3/2015	53	58
11/5/2013	54	54	7/8/2014	43	49	3/10/2015	67	61
11/12/2013	47	53	7/15/2014	41	49	3/17/2015	56	51
11/19/2013	77	54	7/22/2014	47	55	3/24/2015	65	52
11/26/2013	40	38	7/29/2014	59	38	3/31/2015	32	46
12/3/2013	38	54	8/5/2014	41	56	4/7/2015	65	47
12/10/2013	33	46	8/12/2014	66	46	4/14/2015	60	51
12/17/2013	31	54	8/19/2014	53	47	4/21/2015	66	63
12/24/2013	32	72	8/26/2014	53	54	4/28/2015	62	44
12/31/2013	24	64	9/2/2014	59	48	5/5/2015	44	55
1/7/2014	49	53	9/9/2014	48	47	5/12/2015	60	54
1/14/2014	61	43	9/16/2014	59	46	5/19/2015	48	53
1/21/2014	43	43	9/23/2014	57	46	5/26/2015	47	54
1/28/2014	54	61	9/30/2014	43	59	6/2/2015	56	51
2/4/2014	52	50	10/7/2014	56	50	6/9/2015	47	59
2/11/2014	60	56	10/14/2014	30	56	6/16/2015	45	63
2/18/2014	68	63	10/21/2014	52	60	6/23/2015	42	53
2/25/2014	70	55	10/28/2014	60	49	6/30/2015	34	57
3/4/2014	67	67	11/4/2014	55	67	7/7/2015	49	69
3/11/2014	66	44	11/11/2014	50	54	7/14/2015	62	52
3/18/2014	56	53	11/18/2014	41	62	7/21/2015	46	48
3/25/2014	67	54	11/25/2014	37	53	7/28/2015	48	56
4/1/2014	34	46	12/2/2014	52	51	8/4/2015	57	53
4/8/2014	71	48	12/9/2014	52	57	8/11/2015	63	58
4/15/2014	55	56	12/16/2014	53	55	8/18/2015	65	50
4/22/2014	73	52	12/23/2014	43	46	8/25/2015	63	49
4/29/2014	66	56	12/30/2014	40	54	9/1/2015	49	54
5/6/2014	62	46	1/6/2015	60	45	9/8/2015	52	45
5/13/2014	69	64	1/13/2015	78	48	9/15/2015	63	49
5/20/2014	42	49	1/20/2015	53	54	9/22/2015	53	53
5/27/2014	39	46	1/27/2015	55	50			

Table 47: Weekly Discharge Confidence Intervals

Weekly Discharge	**MSU Records 95% CI**	50.625	54.990
	IMPRINT 95% CI	51.625	54.222
	P-Value	0.928	

Appendix G – Overload Threshold Determination

The overload threshold is the VACP value at which a worker is considered overloaded. Overload is defined as the times when a worker is behind on tasks, task performance is suffering, and the worker is losing track of the full picture. A worker cannot sustain work at this level for very long without problems occurring. One nurse and one technician were asked to provide 95% confidence interval for the percentage of a week that is spent overloaded. The percentage of time during a week that nurses and technicians spend over 30, 35, 40, and 45 VACP units were averaged for 60 IMPRINT runs. The 95% confidence intervals for the IMPRINT outputs and SMEs are shown in Table 48. The table shows that the nurse overload for the 4 VACP levels overlap with the SME 95% CI; however, the 35 and 40 VACP level had the closes mean. Technician overload only overlapped with the SME 95% CI at the 30 and 35 VACP level and 35 VACP level having the closes mean. Ultimately, the 35 VACP level was selected as the best fit for the nurse and technician overload threshold. The confidence levels of the SMEs are considerably larger than the confidence levels of the model. This may be due to the model not including as much variability as the real-world. It may also be because the SMEs were not very confident in providing confidence intervals.

Table 48: Overload Confidence Intervals

	Nurse Overload 95% Confidence Interval		Tech Overload 95% Confidence Interval	
SME	2.08%	6.25%	3.47%	9.03%
30 VACP	5.93%	6.27%	6.06%	6.82%
35 VACP	4.71%	4.98%	5.12%	5.81%
40 VACP	3.48%	3.69%	2.56%	2.95%
45 VACP	2.64%	2.84%	0.75%	0.93%

Baseline Model Outputs

The baseline model outputs include throughput and workload metrics. The throughput data, in Table 49, includes weekly discharge, bed utilization, and the number of turned away patients. Workload metrics, shown in Table 50, include idle time, average workload, percent overload, and overload instances. To statistically compare the workload metrics between each staff members, the paired t-tests were performed, as shown in Tables 51-54. Individual task information is included in Table 55.

Table 49: Throughput Metrics (60 Runs)

Baseline		
WeeklyDischarge (3rd weeks of 104 runs)	**Average**	52.92
	Std Dev	6.68
BedUtilization (28 days, 3rd week of 4	**Average**	20.40
	Std Dev	5.17
TurnedAwayPTs (3rd weeks of 104 runs)	**Total**	0.00
	Avg # / week	0.00

Table 50: Workload Metrics (60 Runs)

	Percent of Idle Time in One Week		Average Workload over One Week		Percent of Week Overloaded		Number of Overloaded Instances in One Week	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
Nurse1	36.76%	8.73%	13.26	1.78	5.14%	0.93%	63.13	11.89
Nurse2	39.48%	8.54%	12.61	1.73	4.93%	0.98%	58.18	13.33
Nurse3	41.51%	8.55%	12.23	1.78	4.89%	0.91%	59.10	10.82
Nurse4	43.79%	7.93%	11.73	1.61	4.75%	0.89%	56.77	11.47
Nurse5	46.77%	8.09%	11.21	1.72	4.87%	0.84%	59.17	12.97
Nurse6	48.94%	7.80%	10.68	1.65	4.50%	0.88%	53.95	12.99
Technician1	48.32%	6.00%	10.70	1.60	6.08%	1.98%	127.33	48.10
Technician2	50.48%	5.81%	10.22	1.48	5.74%	1.82%	118.08	40.75
Technician3	51.88%	6.40%	9.78	1.59	5.19%	1.73%	102.27	36.98
Technician4	53.47%	6.45%	9.42	1.63	4.85%	1.82%	98.85	41.33
Charge Nurse	47.48%	1.47%	9.03	0.39	2.07%	0.32%	91.25	16.45
Shift Leader	55.05%	6.37%	8.48	1.51	3.28%	1.38%	73.00	31.91
***Average Weekly Discharge for the 60 runs was 52.68 patients.**								

Table 51: Idle Time Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.000											
Nurse3	0.000	0.001										
Nurse4	0.000	0.000	0.000									
Nurse5	0.000	0.000	0.000	0.000								
Nurse6	0.000	0.000	0.000	0.000	0.000							
Technician1	0.000	0.000	0.000	0.000	0.008	0.308						
Technician2	0.000	0.000	0.000	0.000	0.000	0.006	0.000					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002			
Charge Nurse	0.000	0.000	0.000	0.000	0.454	0.109	0.216	0.000	0.000	0.000		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	

Table 52: Average Workload Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.000											
Nurse3	0.000	0.001										
Nurse4	0.000	0.000	0.000									
Nurse5	0.000	0.000	0.000	0.000								
Nurse6	0.000	0.000	0.000	0.000	0.000							
Technician1	0.000	0.000	0.000	0.000	0.000	0.810						
Technician2	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.036		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	

Table 53: Overload Time Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.212											
Nurse3	0.094	0.821										
Nurse4	0.015	0.309	0.375									
Nurse5	0.073	0.716	0.867	0.365								
Nurse6	0.000	0.007	0.013	0.077	0.011							
Technician1	0.000	0.000	0.000	0.000	0.000	0.000						
Technician2	0.016	0.001	0.000	0.000	0.000	0.000	0.035					
Technician3	0.828	0.252	0.203	0.045	0.101	0.002	0.000	0.001				
Technician4	0.244	0.760	0.859	0.644	0.936	0.083	0.000	0.000	0.039			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
Shift Leader	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Table 54: Overload Instances Paired T-Test

	Nurse1	Nurse2	Nurse3	Nurse4	Nurse5	Nurse6	Technician1	Technician2	Technician3	Technician4	Charge Nurse	Shift Leader
Nurse1												
Nurse2	0.031											
Nurse3	0.036	0.627										
Nurse4	0.002	0.518	0.203									
Nurse5	0.057	0.663	0.972	0.188								
Nurse6	0.000	0.046	0.008	0.162	0.008							
Technician1	0.000	0.000	0.000	0.000	0.000	0.000						
Technician2	0.000	0.000	0.000	0.000	0.000	0.000	0.023					
Technician3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Technician4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.347			
Charge Nurse	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.013	0.099		
Shift Leader	0.009	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Table 55: Task Time Outputs

Nurse 1			
Task	**Overload Time (hrs)**	**Total Time (hrs)**	**Overload Percent**
Administer Meds	5.21	15.05	37%
Close/Turn In Records	0.09	1.36	6%
Complete Admission Notes	0.13	2.39	5%
Full Assessment	4.56	13.82	35%
Handle Call Light	1.94	7.71	24%
Nurse 1 Shift Change	0.15	7.61	2%
Collect Labs	0.07	2.54	3%
Nurse D/C Patient	0.05	0.95	5%
Perform Admission Orders	1.35	6.90	18%
Perform Discharge Orders	0.62	1.59	39%
Prepare Discharge Papers	0.31	1.15	29%
Prepare PT for D/C	0.37	1.70	22%
Preview Orders/Patient Info	0.01	0.75	2%
Q2h Rounding	3.28	53.07	6%
Receive Report	0.20	1.78	11%
Room Prep	0.03	0.90	2%
Strip Room	0.03	1.32	2%

Shift Leader			
Task	**Overload Time (hrs)**	**Total Time (hrs)**	**Overload Percent**
Assign Patient to Tech	0.88	4.36	20%
Handle Call Light	3.80	14.78	25%
Misc Cleaning	0.07	6.12	1%
Q2h Rounding	1.81	20.90	8%
Remove Invasive Devices	0.04	0.80	5%
Restock PT & Supply Rooms	0.11	6.00	2%
Retreive from Test	0.12	2.66	4%
Room Prep	0.05	0.70	6%
Shift Ldr Misc Checks	0.31	4.06	8%
Shift Ldr Shift Change	0.24	4.46	5%
Strip Room	0.04	1.08	4%
Collect Lab	0.15	3.54	4%
Tech D/C Patient	0.04	1.14	4%
Tech, Q Sunday Night Tasks	0.00	0.46	0%
Transport to Test	0.20	2.65	7%
Vitals, I/O, Neuro	5.70	20.85	27%

Technician 1			
Task	**Overload Time (hrs)**	**Total Time (hrs)**	**Overload Percent**
Handle Call Light	6.33	20.03	30%
Q2h Rounding	3.85	30.81	12%
Remove Invasive Devices	0.09	1.20	6%
Retreive from Test	0.30	3.86	7%
Room Prep	0.10	1.17	8%
Strip Room	0.13	1.70	8%
Tech 1 Shift Change	0.02	2.22	1%
Collect Lab	0.48	6.05	8%
Tech D/C Patient	0.14	1.71	7%
Transport to Test	0.40	3.72	9%
Vitals, I/O, Neuro	11.33	31.25	35%

Charge Nurse			
Task	**Overload Time (hrs)**	**Total Time (hrs)**	**Overload Percent**
72 Hour Callbacks	0.24	5.78	4%
Assign Patient to Room/Nurse	3.32	9.96	33%
Bed Meeting (0745, M-F)	0.53	1.39	38%
Charge Rounds	1.32	16.56	8%
Clean Nurse Station (0715/1915)	0.05	2.27	2%
CN Shift Change	0.27	8.19	3%
Handle Call Light	0.59	5.61	10%
Help Visitors/Phone Calls	2.77	48.09	6%
Internal Med Meeting (830, M-F)	0.77	3.32	23%
Nurse, Q Sunday Night Tasks	0.01	0.80	2%
Restock Med Room	0.11	3.08	4%
Update board/journal/WMSN	0.15	10.07	2%

Appendix H – Patient Load Alternate Models

Patient Load Changes

The alternate models represent the MSU under different patient loads. These were created by changing the time between patient arrivals of the baseline model. Equation 2 is the formula used to change the time between patient arrivals. Dividing the baseline model time-between-patient arrival distributions by a patient load multiplier creates proportionately smaller new time-between-patient arrival distributions. The resulting distributions are scaled which results in a new mean and standard deviation. The patient load multiplier values used for each model are shown in Table 56.

$$\boldsymbol{New\ Time\ Between\ Patients = Baseline\ Time\ Between\ Patients \div Patient\ Load\ Multiplier} \tag{2}$$

Table 56: Patient Load Multiplier Values

Model	Patient Load Multiplier Value
Baseline Model	1.0
10% Increase	1.1
20% Increase	1.2
30% Increase	1.3
40% Increase	1.4
50% Increase	1.5

Patient Load Alternate Model Assumptions

In addition to the baseline model assumptions, the alternate models have new assumptions which are shown in Table 57.

Table 57: Patient Load Alternate Model Assumptions

Alternate Model Assumptions	Justification
Patient arrival rate distributions are scaled	It is assumed that the variability would increase along with an increase in the average patient load. The real variability of the alternate models is not known so allowing for increased variability will result in the more extreme results.
Patient attributes remain unchanged	The patients in the alternate models are of the same type and acuity as the baseline model. In reality, an increased patient load could be from a patients with different types of illnesses or severity than the current patients. The alternate models keep the baseline model patient attributes for simplicity.
Model logic remain unchanged	The task logic, durations, and probabilities are the same in the alternate models as they are in the baseline model. In reality, tasks may be performed differently under higher patient loads. The baseline model logic was used in the alternate models for simplicity and because potential changed to the model logic are unknown.
Staffing numbers remain unchanged	The number of medical staff in the alternate models remains the same as the baseline model. The purpose of the alternate models is to evaluate the mental workload demand changes to the staff under higher patient loads. If the number of medical staff members was increased along with the patient loads, there would be little or no changes which would eliminate the purpose of the alternate models.

Patient Load Alternate Model Outputs

The alternate model throughput outputs are shown in Table 58. Idle time outputs and ANOVA results are shown in Tables 59 and 60. Average workload outputs and ANOVA are shown in Tables 61 and 62. Overload time outputs and ANOVA are shown in Tables 63 and 64. Task time values for the baseline, 30% increase and 50% increase are shown in Tables 65-68.

Table 58: Patient Load Alternate Throughput Outputs

		Baseline	10%	20%	30%	40%	50%
WeeklyDischarge	**Average**	52.92	58.45	63.71	67.61	73.69	77.79
(3rd weeks of 104 runs)	**Std Dev**	6.68	6.28	7.35	7.54	7.30	6.81
BedUtilization	**Average**	20.40	21.00	24.32	24.54	29.18	30.46
(28 days, 3rd week of 4	**Std Dev**	5.17	5.03	3.99	5.39	6.04	5.16
TurnedAwayPTs	**Total**	0.00	7.00	26.00	44.00	187.00	232.00
(3rd weeks of 104 runs)	**Avg # / week**	0.00	0.07	0.25	0.42	1.80	2.23

Table 59: Idle Time Outputs (n=60)

Percent of Idle Time in One Week (60 runs)												
	Baseline		10%		20%		30%		40%		50%	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
Weekly Discharge	52.68	7.56	58.75	6.34	63.3	7.13	67.45	7.42	73.53	7.31	77.58	6.21
Nurse1	36.76%	8.73%	30.28%	7.51%	26.34%	7.62%	22.76%	5.63%	17.32%	6.73%	15.82%	5.35%
Nurse2	39.48%	8.54%	33.84%	6.71%	28.32%	8.09%	24.76%	5.49%	19.25%	6.13%	16.82%	5.90%
Nurse3	41.51%	8.55%	35.55%	7.26%	29.64%	8.81%	27.30%	6.91%	20.32%	6.84%	18.86%	5.72%
Nurse4	43.79%	7.93%	37.21%	7.26%	32.28%	7.62%	29.68%	6.69%	23.25%	5.71%	20.65%	6.03%
Nurse5	46.77%	8.09%	40.66%	7.29%	35.40%	8.33%	32.29%	6.92%	26.04%	7.36%	22.79%	6.39%
Nurse6	48.94%	7.80%	42.38%	7.16%	37.70%	8.22%	34.30%	7.16%	27.30%	6.31%	24.98%	6.69%
Technician1	48.32%	6.00%	43.34%	5.00%	40.15%	6.01%	38.15%	4.69%	34.32%	4.70%	32.87%	4.50%
Technician2	50.48%	5.81%	45.45%	4.81%	42.00%	5.41%	40.17%	5.12%	35.81%	4.64%	34.02%	4.77%
Technician3	51.88%	6.40%	47.38%	5.54%	43.97%	5.94%	41.59%	4.38%	37.34%	4.98%	35.93%	5.33%
Technician4	53.47%	6.45%	48.54%	5.40%	45.01%	5.85%	43.36%	4.49%	38.61%	5.25%	37.02%	4.76%
Charge Nurse	47.48%	1.47%	46.40%	1.29%	45.38%	1.34%	44.63%	1.35%	43.35%	1.41%	42.54%	1.34%
Shift Leader	55.05%	6.37%	49.95%	6.12%	46.47%	6.31%	44.08%	5.69%	39.51%	5.20%	38.14%	4.28%

Table 60: Idle Time ANOVA (n=60)

	Nurse1		Technician1		Charge Nurse		Shift Leader	
	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA
Baseline	(0.34980, 0.38550)	A	(0.47005, 0.49640)	A	(0.47130, 0.47825)	A	(0.53601, 0.56499)	A
10%	(0.28493, 0.32061)	B	(0.42027, 0.44662)	B	(0.46051, 0.46746)	B	(0.48502, 0.51400)	B
20%	(0.24558, 0.28126)	C	(0.38833, 0.41468)	C	(0.45036, 0.45731)	C	(0.45024, 0.47922)	C
30%	(0.20979, 0.24547)	C	(0.36837, 0.39472)	C	(0.44284, 0.44979)	D	(0.42634, 0.45532)	C
40%	(0.15536, 0.19104)	D	(0.33000, 0.35635)	D	(0.42999, 0.43694)	E	(0.38059, 0.40957)	D
50%	(0.14032, 0.17600)	D	(0.31552, 0.34187)	D	(0.42187, 0.42883)	F	(0.36691, 0.39589)	D

Table 61: Average Workload Outputs (n=60)

Average Workload over One Week (60 runs)												
	Baseline		10%		20%		30%		40%		50%	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
Weekly Discharge	52.68	7.56	58.75	6.34	63.3	7.13	67.45	7.42	73.53	7.31	77.58	6.21
Nurse1	13.26	1.78	14.61	1.52	15.49	1.56	16.29	1.17	17.34	1.36	17.73	1.12
Nurse2	12.61	1.73	13.88	1.39	14.93	1.66	15.78	1.17	16.93	1.18	17.52	1.19
Nurse3	12.23	1.78	13.54	1.59	14.74	1.79	15.23	1.43	16.74	1.41	17.06	1.16
Nurse4	11.73	1.61	13.14	1.44	14.23	1.55	14.74	1.39	16.09	1.21	16.72	1.28
Nurse5	11.21	1.72	12.48	1.52	13.54	1.77	14.32	1.46	15.59	1.50	16.26	1.36
Nurse6	10.68	1.65	12.10	1.48	13.14	1.69	13.82	1.49	15.22	1.25	15.82	1.38
Technician1	10.70	1.60	11.96	1.40	12.91	1.71	13.38	1.32	14.68	1.37	14.93	1.28
Technician2	10.22	1.48	11.43	1.30	12.40	1.45	12.91	1.37	14.17	1.36	14.71	1.39
Technician3	9.78	1.59	10.93	1.40	11.91	1.59	12.49	1.24	13.74	1.36	14.14	1.48
Technician4	9.42	1.63	10.68	1.42	11.58	1.53	12.03	1.27	13.37	1.46	13.81	1.33
Charge Nurse	9.03	0.39	9.38	0.37	9.66	0.43	9.84	0.42	10.26	0.38	10.46	0.39
Shift Leader	8.48	1.51	9.69	1.53	10.61	1.62	11.21	1.47	12.44	1.46	12.85	1.14

Table 62: Average Workload ANOVA (n=60)

	Nurse1		Technician1		Charge Nurse		Shift Leader	
	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA
Baseline	(12.900, 13.629)	A	(10.336, 11.074)	A	(8.927, 9.127)	A	(8.109, 8.853)	A
10%	(14.248, 14.977)	B	(11.593, 12.332)	B	(9.279, 9.479)	B	(9.319, 10.062)	B
20%	(15.122, 15.851)	C	(12.545, 13.283)	C	(9.563, 9.763)	C	(10.236, 10.979)	C
30%	(15.928, 16.657)	D	(13.009, 13.747)	C	(9.744, 9.945)	C	(10.836, 11.579)	C
40%	(16.974, 17.703)	E	(14.312, 15.050)	D	(10.157, 10.358)	D	(12.067, 12.810)	D
50%	(17.364, 18.093)	E	(14.562, 15.300)	D	(10.360, 10.560)	D	(12.474, 13.217)	D

Table 63: Overload Time Outputs (n=60)

Percentage of Week Overloaded (60 runs)												
	Baseline		10%		20%		30%		40%		50%	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
Weekly Discharge	52.68	7.56	58.75	6.34	63.30	7.13	67.45	7.42	73.53	7.31	77.58	6.21
Nurse1	5.14%	0.93%	5.55%	0.99%	5.86%	0.99%	6.21%	0.95%	6.06%	1.02%	6.41%	1.02%
Nurse2	4.93%	0.98%	5.47%	0.81%	5.45%	0.95%	5.98%	1.07%	6.15%	1.11%	6.42%	1.08%
Nurse3	4.89%	0.91%	5.42%	0.98%	5.57%	1.01%	5.63%	0.94%	6.31%	1.00%	6.27%	0.90%
Nurse4	4.75%	0.89%	5.17%	0.87%	5.58%	0.95%	5.64%	0.86%	5.89%	0.97%	6.27%	1.06%
Nurse5	4.87%	0.84%	5.26%	0.99%	5.41%	1.10%	5.93%	1.00%	6.01%	0.97%	6.15%	0.98%
Nurse6	4.50%	0.88%	5.01%	1.00%	5.45%	1.00%	5.45%	0.89%	5.76%	0.95%	6.07%	0.94%
Technician1	6.08%	1.98%	7.40%	1.87%	8.81%	2.39%	9.25%	1.88%	11.18%	1.99%	11.29%	1.83%
Technician2	5.74%	1.82%	6.88%	1.68%	8.10%	1.91%	8.83%	1.81%	10.33%	2.05%	11.25%	1.99%
Technician3	5.19%	1.73%	6.36%	1.65%	7.72%	2.03%	8.20%	1.66%	9.89%	1.82%	10.49%	1.94%
Technician4	4.85%	1.82%	6.24%	1.73%	7.27%	1.77%	7.76%	1.92%	9.37%	1.89%	10.07%	1.91%
Charge Nurse	2.07%	0.32%	2.34%	0.32%	2.47%	0.41%	2.52%	0.45%	2.86%	0.39%	2.94%	0.45%
Shift Leader	3.28%	1.38%	4.24%	1.64%	5.25%	1.76%	5.84%	1.62%	7.13%	1.89%	7.60%	1.46%

Table 64: Overload Time ANOVA (n=60)

	Nurse1		Technician1		Charge Nurse		Shift Leader	
	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA	95% CI	ANOVA
Baseline	(0.04889, 0.05388)	A	(0.05571, 0.06586)	A	(0.019719, 0.021707)	A	(0.02863, 0.03693)	A
10%	(0.05300, 0.05800)	AB	(0.06890, 0.07905)	B	(0.022358, 0.024346)	B	(0.03824, 0.04654)	B
20%	(0.05611, 0.06110)	BC	(0.08304, 0.09318)	C	(0.023729, 0.025717)	B	(0.04831, 0.05661)	C
30%	(0.05962, 0.06462)	CD	(0.08738, 0.09753)	C	(0.024189, 0.026177)	B	(0.05420, 0.06250)	C
40%	(0.05807, 0.06307)	BCD	(0.10674, 0.11689)	D	(0.027568, 0.029556)	C	(0.06718, 0.07549)	D
50%	(0.06159, 0.06659)	D	(0.10781, 0.11796)	D	(0.028420, 0.030409)	C	(0.07184, 0.08014)	D

Table 65: Nurse1 Tasks Times (n=10)

	Baseline			30% Increase			50% Increase		
Task	**Overload Time (hrs)**	**Total Time (hrs)**	**%**	**Overload Time (hrs)**	**Total Time (hrs)**	**%**	**Overload Time (hrs)**	**Total Time (hrs)**	**%**
Administer Meds	5.21	15.05	37%	5.15	18.84	28%	4.86	20.24	25%
Close/Turn In Records	0.09	1.36	6%	0.24	1.80	13%	0.35	2.02	17%
Complete Admission Notes	0.13	2.39	5%	0.23	3.56	7%	0.22	3.71	6%
Full Assessment	4.56	13.82	35%	4.23	16.23	27%	4.09	18.24	23%
Handle Call Light	1.94	7.71	24%	2.93	9.37	31%	3.58	9.65	37%
Nurse 1 Shift Change	0.15	7.61	2%	0.35	7.61	4%	0.33	6.91	5%
Collect Labs	0.07	2.54	3%	0.13	3.68	4%	0.24	3.56	7%
Nurse D/C Patient	0.05	0.95	5%	0.02	1.24	2%	0.07	1.10	8%
Perform Admission Orders	1.35	6.90	18%	2.54	9.41	26%	2.92	10.13	28%
Perform Discharge Orders	0.62	1.59	39%	1.15	2.21	54%	1.48	2.39	61%
Prepare Discharge Papers	0.31	1.15	29%	0.51	1.73	29%	0.36	1.70	21%
Prepare PT for D/C	0.37	1.70	22%	0.49	2.28	22%	0.59	2.33	25%
Preview Orders/Patient Info	0.01	0.75	2%	0.07	1.06	7%	0.06	1.22	4%
Q2h Rounding	3.28	53.07	6%	4.06	62.03	7%	4.11	67.63	6%
Receive Report	0.20	1.78	11%	0.66	2.64	24%	0.72	2.70	27%
Room Prep	0.03	0.90	2%	0.07	1.31	5%	0.01	1.36	1%
Strip Room	0.03	1.32	2%	0.10	1.83	6%	0.12	1.89	6%
Total	18.38	120.58	15%	22.93	146.83	16%	24.10	156.76	15%

Table 66: Technician 1 Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
Handle Call Light	6.33	20.03	30%	10.00	25.99	38%	11.90	29.26	41%
Q2h Rounding	3.85	30.81	12%	6.06	39.47	15%	6.53	42.25	15%
Remove Invasive Devices	0.09	1.20	6%	0.19	1.51	13%	0.19	1.88	10%
Retreive from Test	0.30	3.86	7%	0.61	4.49	13%	0.64	5.24	12%
Room Prep	0.10	1.17	8%	0.21	1.35	15%	0.27	1.69	15%
Strip Room	0.13	1.70	8%	0.23	2.00	10%	0.37	2.50	15%
Tech 1 Shift Change	0.02	2.22	1%	0.03	2.13	1%	0.06	2.21	3%
Collect Lab	0.48	6.05	8%	0.43	6.43	7%	0.62	7.29	9%
Tech D/C Patient	0.14	1.71	7%	0.24	2.03	12%	0.31	2.68	14%
Transport to Test	0.40	3.72	9%	0.56	4.64	12%	0.79	5.40	15%
Vitals, I/O, Neuro	11.33	31.25	35%	16.32	39.49	41%	19.20	43.67	44%
Total	23.18	103.71	22%	34.87	129.53	27%	40.87	144.07	28%

Table 67: Charge Nurse Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
72 Hour Callbacks	0.24	5.78	4%	0.25	7.31	4%	0.32	8.03	4%
Assign Patient to Room/Nurse	3.32	9.96	33%	4.27	12.55	33%	5.37	14.80	36%
Bed Meeting (0745, M-F)	0.53	1.39	38%	0.54	1.47	37%	0.61	1.50	40%
Charge Rounds	1.32	16.56	8%	1.53	15.68	10%	1.88	17.20	11%
Clean Nurse Station (0715/1915)	0.05	2.27	2%	0.05	2.31	2%	0.06	2.39	3%
CN Shift Change	0.27	8.19	3%	0.51	8.18	6%	0.67	8.13	8%
Handle Call Light	0.59	5.61	10%	0.98	7.37	13%	1.26	7.36	16%
Help Visitors/Phone Calls	2.77	48.09	6%	3.25	48.19	7%	3.94	47.78	8%
Internal Med Meeting (830)	0.77	3.32	23%	0.87	3.24	27%	0.95	3.32	29%
Nurse, Q Sunday Night Tasks	0.01	0.80	2%	0.01	0.72	1%	0.00	0.75	0%
Restock Med Room	0.11	3.08	4%	0.16	3.15	5%	0.14	3.10	5%
Update board/journal/WMSN	0.15	10.07	2%	0.25	13.26	2%	0.40	15.01	3%
Total	10.13	115.11	9%	12.68	123.43	10%	15.60	129.36	12%

Table 68: Shift Leader Tasks Times (n=10)

Task	Baseline			30% Increase			50% Increase		
	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%	Overload Time (hrs)	Total Time (hrs)	%
Assign Patient to Tech	0.88	4.36	20%	1.57	5.84	26%	1.96	6.72	29%
Handle Call Light	3.80	14.78	25%	6.08	17.60	33%	7.75	21.37	36%
Misc Cleaning	0.07	6.12	1%	0.13	6.09	2%	0.27	5.71	5%
Q2h Rounding	1.81	20.90	8%	3.32	27.27	12%	4.00	31.94	13%
Remove Invasive Devices	0.04	0.80	5%	0.10	1.08	10%	0.15	1.34	11%
Restock PT & Supply Rooms	0.11	6.00	2%	0.21	5.91	3%	0.30	5.93	5%
Retreive from Test	0.12	2.66	4%	0.31	3.77	8%	0.50	3.66	14%
Room Prep	0.05	0.70	6%	0.15	0.99	14%	0.17	1.18	14%
Shift Ldr Misc Checks	0.31	4.06	8%	0.85	4.03	21%	0.53	4.07	13%
Shift Ldr Shift Change	0.24	4.46	5%	0.67	4.53	15%	0.37	4.35	9%
Strip Room	0.04	1.08	4%	0.11	1.36	8%	0.19	1.71	12%
Collect Lab	0.15	3.54	4%	0.28	4.77	5%	0.33	4.69	7%
Tech D/C Patient	0.04	1.14	4%	0.05	1.04	4%	0.25	1.71	15%
Tech, Q Sunday Night Tasks	0.00	0.46	0%	0.00	0.47	0%	0.01	0.47	2%
Transport to Test	0.20	2.65	7%	0.52	3.86	12%	0.53	3.85	14%
Vitals, I/O, Neuro	5.70	20.85	27%	7.99	27.57	29%	11.39	31.69	36%
Total	13.56	94.54	14%	22.33	116.19	19%	28.69	130.40	22%

Appendix I – Task Sharing Alternate Models

Task Sharing Changes

To create the task sharing alternate models, the researchers modified the 30% patient load increase model. The 30% patient load increase was modified because it is the patient load which is expected at the MSU. The original "Q2h rounding" task shown in Figure 23 was changed to the task network shown in Figure 24. In the alternate model, only a staff member who is not performing any tasks can start the "Q2h rounding" task for a patient. The assigned staff members is the first staff member who is eligible to perform the task. If they are busy at the moment, the next staff member in the list is checked. This continues (and loops to the top of this list if needed) until a staff member is selected.

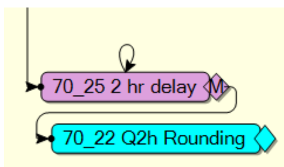

Figure 23: Baseline Model "Q2h Rounding" Task Network

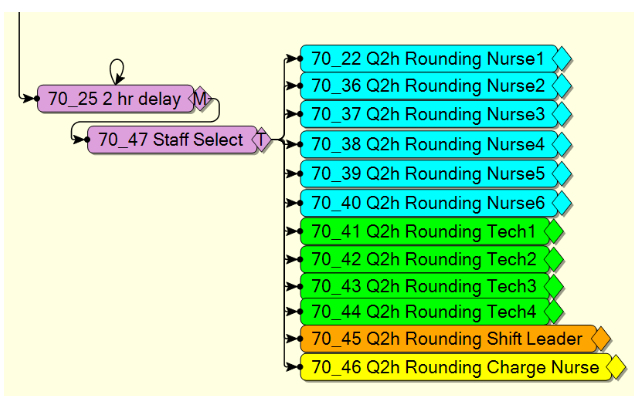

Figure 24: Alternate Model "Q2h Rounding" Task Network

Task Sharing Alternate Model Outputs

To ensure that differences between the baseline and alternate models are due to task sharing and not differences in patient load, the weekly discharge metric was validated in Table 69. The results, differences, and p-value for the idle time, average workload, and overload time are shown in Tables 70-72. The task times are included in Tables 73-76.

Table 69: Weekly Discharge Validation (n=30)

	Baseline Model (30% Increase)	Alternate Model (Task Sharing)
Weekly Discharge	58	65
	65	73
	64	70
	75	72
	80	72
	68	74
	67	53
	54	74
	74	67
	77	65
	68	68
	73	66
	74	62
	72	70
	68	79
	73	61
	65	70
	55	73
	69	58
	64	78
	64	69
	69	84
	71	84
	68	92
	68	65
	67	70
	67	68
	63	77
	78	58
	67	67
Average	68.17	70.13
SD	6.11	8.24
P-value	0.298	

Table 70: Idle Time Results (n=30)

	Baseline Model		Alternate Model			
	Mean	SD	Mean	SD	Difference	P-value
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	22.43%	4.40%	33.12%	6.78%	10.68%	0.000
Nurse2	24.39%	5.27%	30.70%	5.96%	6.32%	0.000
Nurse3	28.07%	6.18%	29.97%	5.68%	1.89%	0.222
Nurse4	29.02%	6.68%	29.89%	5.88%	0.87%	0.594
Nurse5	32.32%	6.07%	30.54%	6.15%	-1.78%	0.264
Nurse6	33.73%	6.79%	31.11%	6.44%	-2.63%	0.130
Technician1	37.88%	4.28%	32.62%	5.97%	-5.26%	0.000
Technician2	39.59%	4.57%	33.92%	6.67%	-5.67%	0.000
Technician3	41.67%	4.12%	34.84%	6.60%	-6.84%	0.000
Technician4	42.90%	4.54%	36.91%	6.59%	-5.98%	0.000
Charge Nurse	44.57%	1.34%	34.35%	3.96%	-10.22%	0.000
Shift Leader	44.14%	4.47%	37.37%	6.80%	-6.77%	0.000
Average	35.06%	-	32.94%	-	-2.11%	0.115

Table 71: Average Workload Results (n=30)

	Baseline Model		Alternate Model			
	Mean	SD	Mean	SD	Difference	P-value
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	16.37	0.97	14.64	1.67	-1.73	0.000
Nurse2	15.86	1.11	14.84	1.48	-1.02	0.004
Nurse3	15.07	1.34	14.98	1.53	-0.09	0.802
Nurse4	14.93	1.36	14.81	1.39	-0.13	0.717
Nurse5	14.34	1.23	14.75	1.53	0.41	0.258
Nurse6	13.96	1.35	14.35	1.56	0.39	0.301
Technician1	13.46	1.22	15.12	1.74	1.67	0.000
Technician2	13.07	1.23	14.77	1.92	1.70	0.000
Technician3	12.43	1.19	14.39	1.93	1.96	0.000
Technician4	12.04	1.25	13.96	1.81	1.92	0.000
Charge Nurse	9.85	0.43	12.45	1.07	2.59	0.000
Shift Leader	11.14	1.15	13.11	1.87	1.97	0.000
Average	13.54	-	14.35	-	0.80	0.021

Table 72: Overload Time Results (n=30)

	Baseline Model		Alternate Model			
	Mean	SD	Mean	SD	Difference	P-value
Weekly Discharge	68.17	6.11	70.13	8.24	1.97	0.298
Nurse1	6.21%	1.16%	6.16%	1.15%	-0.05%	0.860
Nurse2	6.01%	1.07%	5.54%	1.14%	-0.47%	0.108
Nurse3	5.73%	0.83%	5.60%	1.00%	-0.13%	0.571
Nurse4	5.77%	0.97%	5.05%	0.94%	-0.71%	0.005
Nurse5	6.02%	0.95%	5.36%	0.88%	-0.66%	0.007
Nurse6	5.46%	0.67%	4.64%	0.96%	-0.83%	0.000
Technician1	9.25%	1.78%	11.23%	2.60%	1.97%	0.001
Technician2	9.05%	1.53%	10.80%	2.65%	1.75%	0.003
Technician3	7.99%	1.60%	9.95%	2.50%	1.95%	0.001
Technician4	7.46%	1.65%	9.70%	2.25%	2.24%	0.000
Charge Nurse	2.52%	0.45%	2.94%	0.42%	0.42%	0.000
Shift Leader	5.59%	1.25%	7.46%	2.24%	1.87%	0.000
Average	6.42%	-	7.04%	-	0.61%	0.019

Table 73: Nurse1 Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Administer Meds	5.15	18.84	28%	5.53	20.88	27%
Close/Turn In Records	0.24	1.80	13%	0.15	1.73	9%
Complete Admission Notes	0.23	3.56	7%	0.18	2.98	6%
Full Assessment	4.23	16.23	27%	5.44	17.53	32%
Handle Call Light	2.93	9.37	31%	2.60	9.66	26%
Nurse 1 Shift Change	0.35	7.61	4%	0.23	7.59	3%
Collect Labs	0.13	3.68	4%	0.17	3.36	4%
Nurse D/C Patient	0.02	1.24	2%	0.04	1.22	3%
Perform Admission Orders	2.54	9.41	26%	1.51	8.41	17%
Perform Discharge Orders	1.15	2.21	54%	1.00	2.06	50%
Prepare Discharge Papers	0.51	1.73	29%	0.45	1.63	28%
Prepare PT for D/C	0.49	2.28	22%	0.58	2.12	28%
Preview Orders/Patient Info	0.07	1.06	7%	0.04	0.93	5%
Q2h Rounding	4.06	62.03	7%	1.19	41.46	3%
Receive Report	0.66	2.64	24%	0.41	2.22	19%
Room Prep	0.07	1.31	5%	0.02	1.06	1%
Strip Room	0.10	1.83	6%	0.08	1.60	5%
Total	**22.93**	**146.83**	**16%**	**19.61**	**126.43**	**16%**

Table 74: Technician1 Task Times (n=10)

Task	Technician 1					
	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Handle Call Light	10.00	25.99	38%	11.46	27.01	42%
Q2h Rounding	6.06	39.47	15%	8.61	53.23	16%
Remove Invasive Devices	0.19	1.51	13%	0.18	1.59	11%
Retreive from Test	0.61	4.49	13%	0.76	5.06	15%
Room Prep	0.21	1.35	15%	0.18	1.44	12%
Strip Room	0.23	2.00	10%	0.29	2.11	14%
Tech 1 Shift Change	0.03	2.13	1%	0.03	2.20	1%
Collect Lab	0.43	6.43	7%	0.59	6.73	8%
Tech D/C Patient	0.24	2.03	12%	0.15	1.76	8%
Transport to Test	0.56	4.64	12%	0.77	5.18	15%
Vitals, I/O, Neuro	16.32	39.49	41%	19.25	41.01	47%
Total	**34.87**	**129.53**	**27%**	**42.27**	**147.30**	**29%**

Table 75: Charge Nurse Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
72 Hour Callbacks	0.25	7.31	4%	0.20	7.05	3%
Assign Patient to Room/Nurse	4.27	12.55	33%	4.96	12.76	39%
Bed Meeting (0745, M-F)	0.54	1.47	37%	0.53	1.46	36%
Charge Rounds	1.53	15.68	10%	1.76	16.27	11%
Clean Nurse Station (0715/1915)	0.05	2.31	2%	0.04	2.32	2%
CN Shift Change	0.51	8.18	6%	0.42	8.00	5%
Handle Call Light	0.98	7.37	13%	1.34	6.90	18%
Help Visitors/Phone Calls	3.25	48.19	7%	3.91	47.91	8%
Internal Med Meeting (830, M-F)	0.87	3.24	27%	0.97	3.33	29%
Nurse, Q Sunday Night Tasks	0.01	0.72	1%	0.00	0.84	1%
Q2h Rounding	0.00	0.00	0%	0.75	24.13	3%
Restock Med Room	0.16	3.15	5%	0.14	3.10	4%
Update board/journal/WMSN	0.25	13.26	2%	0.28	13.35	2%
Total	**12.68**	**123.43**	**10%**	**15.30**	**147.42**	**10%**

Table 76: Shift Leader Task Times (n=10)

Task	Baseline Model			Alternate Model		
	Overload Time (hrs)	Total Time (hrs)	Overload Percent	Overload Time (hrs)	Total Time (hrs)	Overload Percent
Assign Patient to Tech	1.57	5.84	26%	1.60	5.85	27%
Handle Call Light	6.08	17.60	33%	7.48	19.72	38%
Misc Cleaning	0.13	6.09	2%	0.30	6.20	5%
Q2h Rounding	3.32	27.27	12%	5.29	40.40	13%
Remove Invasive Devices	0.10	1.08	10%	0.13	0.97	15%
Restock PT & Supply Rooms	0.21	5.91	3%	0.25	6.14	4%
Retreive from Test	0.31	3.77	8%	0.44	3.74	11%
Room Prep	0.15	0.99	14%	0.13	0.89	14%
Shift Ldr Misc Checks	0.85	4.03	21%	0.72	4.18	17%
Shift Ldr Shift Change	0.67	4.53	15%	0.59	4.51	13%
Strip Room	0.11	1.36	8%	0.10	1.34	7%
Collect Lab	0.28	4.77	5%	0.47	4.39	12%
Tech D/C Patient	0.05	1.04	4%	0.16	1.43	10%
Tech, Q Sunday Night Tasks	0.00	0.47	0%	0.01	0.53	3%
Transport to Test	0.52	3.86	12%	0.45	3.81	11%
Vitals, I/O, Neuro	7.99	27.57	29%	11.56	30.21	37%
Total	**22.33**	**116.19**	**19%**	**29.67**	**134.30**	**22%**

Bibliography

Alion Science and Technology Corporation. (2015a). IMPRINT PRO. Boulder, Colorado: Alion Science and Technology.

Alion Science and Technology Corporation. (2015b). IMPRINT Pro User Guide. Boulder, Colorado: Alion Science and Technology.

Barber, B. (2015). Wright-Patterson Agreement to Expand Treatment for VA Patients. Retrieved July 13, 2015, from http://www.military.com/daily-news/2015/04/30/wright-patterson-agreement-to-expand-treatment-for-va-patients.html

Bierbaum, C. R., Szabo, S. M., & Aldrich, T. B. (1989). *Task analysis of the UH-60 mission and decision rules for developing a UH-60 workload prediction model*. Alexandria, VA.

Brailsford, S. C. (2007). Tutorial: Advances and Challenges in Healthcare Simulation Modeling. In *2007 Winter Simulation Conference* (pp. 1436–1448). IEEE Press.

Carey, R. G., & Lloyd, R. C. (1995). *Measuring quality improvement in healthcare: a guide to statistical process control applications*. ASQ Quality Press.

Center for Health Workforce Studies School of Public Health. (2006). *The Impact of the Aging Population on the Health Workforce in the United States: Summary of Key Findings*. Rensselaer, NY.

Colby, S. L., & Ortman, J. M. (2014). *Projections of the size and composition of the US population: 2014 to 2060*. Washington, DC. Retrieved from http://www.census.gov/content/dam/Census/library/publications/2015/demo/p25-1143.pdf

Davies, R., & Davies, H. (1994). Modelling patient flows and resource provision in health systems. *Omega*, *22*(2), 123–131.

Deming, E. W. (2000). *Out of the Crisis*. The MIT Press.

Duguay, C., & Chetouane, F. (2007). Modeling and Improving Emergency Department Systems using Discrete Event Simulation. *Simulation*, *83*(4), 311–320.

Feddock, C. a, Hoellein, A. R., Griffith, C. H., Wilson, J. F., Becker, N. S., Bowerman, J. L., & Caudill, T. S. (2005). Are continuity clinic patients less satisfied when residents have a heavy inpatient workload? *Evaluation & the Health Professions*, *28*(4), 390–399. http://doi.org/10.1177/0163278705281070

Ferrin, D. M., Miller, M. J., & McBroom, D. L. (2007). Maximizing hospital finanacial impact and emergency department throughput with simulation. In *Proceedings - Winter Simulation Conference* (pp. 1566–1573). Piscataway, NJ: IEEE Computer Society Press.

Forrester, J. (1997). System Dynamics. Retrieved January 1, 2016, from http://web.mit.edu/sysdyn/sd-intro/index.html

Graban, M. (2011). *Lean Hospitals: Improving Quality, Patient Safety, and Employee Engagement, Second Edition* (2nd ed.). Productivity Press.

Gunal, M., & Pidd, M. (2010). Discrete event simulation for performance modelling in healthcare: a review of the literature. *Journal of Simulation*, *4*(1), 42–51.

Gurses, A. P., Carayon, P., & Wall, M. (2009). Impact of performance obstacles on intensive care nurses' workload, perceived quality and safety of care, and quality of working life. *Health Services Research*, *44*(2P1), 422–443.

Harriott, C. E., Zhuang, R., Adams, J. A., & Deloach, S. A. (2012). Towards Using

Human Performance Moderator Functions in Human-Robot Teams. In *Proceedings of the Human-Agent Interaction Design and Models Workshop*.

Hill, R. R., Miller, J. O., & McIntyre, G. A. (2001). Applications of discrete event simulation modeling to military problems. In *Proceeding of the 2001 Winter Simulation Conference* (Vol. 1).

Hintzen, B. L., Knoer, S. J., Van Dyke, C. J., & Milavitz, B. S. (2009). Effect of lean process improvement techniques on a university hospital inpatient pharmacy. *American Journal of Health-System Pharmacy*, *66*(22), 2042–2047. http://doi.org/10.2146/ajhp080540

Hoyer, M., & Brook, T. V. (2014). New data show long wait times remain at many VA hospitals. Retrieved July 13, 2015, from http://www.usatoday.com/story/news/politics/2014/11/16/long-wait-times-persist-at-many-va-hospitals/19033789/

James, J. T. (2013). A new, evidence-based estimate of patient harms associated with hospital care. *Journal of Patient Safety*, *9*(3), 122–128.

Koh, H. C., & Tan, G. (2005). Data Mining Applications in Healthcare. *Journal of Healthcare Information Management*, *19*(2), 64–72. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/15869215

Kohn, L. T., Corrigan, J. M., & Donaldson, M. S. (1999). To Err is Human: Building a Safer Health System. *Institute of Medicine,* 1–14.

Komashie, A., & Mousavi, A. (2005). Modeling emergency departments using discrete event simulation techniques. In *Proceedings of the 2005 Winter Simulation Conference* (pp. 2681–2685). Piscataway, NJ: IEEE. Retrieved from

http://dl.acm.org/citation.cfm?id=1163203

Lamm, M. H., Eckel, S., Daniels, R., & Amerine, L. B. (2015). Using lean principles to improve outpatient adult infusion clinic chemotherapy preparation turnaround times. *American Journal of Health-System Pharmacy*, *72*(13), 1138–1146. http://doi.org/10.2146/ajhp140453

Liker, J. K. (2004). *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*. *History*. New York: McGraw-Hill.

McCracken, J. H., & Aldrich, T. B. (1984). Analyses of Selected LHX Mission Functions: Implications for Operator Workload and System Automation Goals. Fort Rucker: Anacapa Sciences.

Mitchell, D. K. (2000). Mental Workload and ARL Workload Modeling Tools. Army Research Lab Aberdeen Proving Ground MD.

Mort, J. A. (2015). Clinical Nurse Specialist, 88th Medical Group, Wright-Patterson AFB, OH. Electronic Message.

Mustafee, N., Katsaliaki, K., & Taylor, S. J. E. (2010). Profiling Literature in Healthcare Simulation. *Simulation*, *86*(8-9), 543–558. http://doi.org/10.1177/0037549709359090

Naik, T., Duroseau, Y., Zehtabchi, S., Rinnert, S., Payne, R., McKenzie, M., & Legome, E. (2012). A Structured Approach to Transforming a Large Public Hospital Emergency Department via Lean Methodologies. *Journal for Healthcare Quality*, *34*(2), 86–97. http://doi.org/10.1111/j.1945-1474.2011.00181.x

Park, S., & Leemis, L. (1999). Discrete-Event Simulation : A First Course Technical Attractions of. College of William & Marry. Retrieved from

http://www.cs.wm.edu/~esmirni/Teaching/cs526/DESAFC-1.1.pdf

Rusnock, C. F., & Geiger, C. D. (2013). Using Discrete-Event Simulation for Cognitive Workload Modeling and System Evaluation. In *IIE Annual Conference* (p. 2485). Institute of Industrial Engineers-Publisher.

Scholtes, P. R., Joiner, B. L., & Streibel, B. J. (2003). *The Team Handbook Third Edition*. Oriel Inc.

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Syst.*, *52*(4), 802–815.

Teigen, K. H. (1994). Yerkes-Dodson: A Law for all Seasons. *Theory & Psychology*, *4*(4), 525–547.

Weissman, J. S., Rothschild, J. M., Bendavid, E., Sprivulis, P., Cook, E. F., Evans, R. S., … Bates, D. W. (2007). Hospital workload and adverse events. *Medical Care*, *45*(5), 448–455.

Yahia, Z., Harraz, N., & Eltawil, A. B. (2014). Building Master Surgery Schedules with Leveled Bed Occupancy and Nurse Workloads. In *2014 IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 89–93). http://doi.org/10.1109/IEEM.2014.7058606

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Physchology*, 459–482.

REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
24-03-2016	Master's Thesis	October 2014 – March 2016

TITLE AND SUBTITLE	
Analysis of Inpatient Hospital Staff Mental Workload by Means of Discrete-event Simulation	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Maxheimer, Erich W., 2d Lt, USAF	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 WPAFB OH 45433-7765	AFIT-ENV-MS-16-M-166
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)** **88th MDG MSU**
88th Medical Group, Medical Surgical Unit 4881 Sugar Maple Dr, Dayton OH 45433 423-539-2583, amanda.anderson.11@us.af.mil ATTN: Capt Amanda Anderson	**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRUBTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Many process improvement tools have been applied to the healthcare industry to improve safety and efficiency. However, nearly all of these tools have neglected to explicitly quantify mental workload of healthcare providers despite the consensus that it is related to human performance. This research uses the Improved Performance Research Integration Tool (IMPRINT), a discrete-event simulation (DES), to quantify mental workload. Specifically, this research examines staff members in an inpatient unit at the Wright-Patterson Medical Center to detect workload differences between staff, identify trends which lead to high workload demands, evaluate the influence of patient load on mental workload, and test a workload-leveling process improvement. Results from this study indicate workload differences between staff types and finds that task urgency and complexity play a role in the overloading of tasks. The relationship between predicted mental workload and increased patient load is mostly linear; however, the slopes are different between staff types, indicating that staff types are predicted to be affected unequally by increases in patient demand. Lastly, the task sharing process improvement provides mixed results; idle time and average workload become more balanced, but overload time becomes more unbalanced. Overall, this study demonstrates the usefulness of IMPRINT at evaluating medical systems.

15. SUBJECT TERMS
Healthcare, Discrete-Event Simulation, IMPRINT, Process Improvement

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
					Maj Christina Rusnock, AFIT/ENV
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	U	UU	168	(937) 255-3636, ext 4611 christina.rusnock@afit.edu

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18